Selection of Machining Parameters of Face Milling operation for Aluminium with HSS cutter using Response Surface Methodology and Genetic Algorithm

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ABSTRACT

Components used in chemical equipments are produced from forging, extrusion and casting processes with classic dimension tolerances due to its producing ability. So machining processes were introduced for close tolerance assembly and improve the product working efficiencies. At present, lot of machining processes are available for producing chemical equipments such as turning, milling, drilling and grinding etc.,. Milling operation is playing critical role on making the chemical equipment's components with high accuracy and higher productivity. Face milling operation is one of the milling processes which is used for achieving higher flatness and surface finish of chemical equipment's parts. This work concentrates the parameters influence on Material Removal Rate (MRR) and Surface Roughness (SR) by using aluminium as work piece material. Actually, aluminium alloy has the most significant in chemical industries because of its inherent properties such as, corrosive resistance , low weight to strength ratio. The milling parameters such as feed rate, spindle speed and depth of cut are selected as parameters for improving the quality and productivity. This work put together the link between input and response variables for developing the face milling performances. The Response Surface Methodology (RSM) is employ for making the link between dependent and independent variables. Building the empirical model by conducting regression analysis The performance of developed regression models are verified with experimental results. Verification results show the developed models have best agreement with experimental results. The developed models are used for achieving the best input parameters by using Genetic Algorithm (GA). Finally, the optimal parameters are evaluated by GA.

Indexing terms/Keywords

Face milling parameters, Response Surface Methodolog, Material Removal Rate, Surface Roughness, Genetic Algorithm.

Indexing terms/Keywords

Face milling Processes, Regression Analysis, Aluminium, Analysis of variance, Evolutionary Algorithm

Academic Discipline And Sub-Disciplines

Mechanical Engineering, Chemical Engineering

SUBJECT CLASSIFICATION

Manufacturing,Face milling, Optimization

TYPE (METHOD/APPROACH)

Experimental investigation and its analysis

1. INTRODUCTION

Machining process have been the core of the manufacturing industry [1]. Milling is one of the important machining processes, which producing smooth, helical and contoured surfaces by using multipoint revolving cutting tool called milling cutter. Milling is a versatile and useful machining operation [2 -7].Milling is the most common process in manufacturing setups. The spindle speed of milling cutter and the rate of work piece movements are based on the workpiece and tool materials. Similarly more than two cutting edges in milling cutter give higher MRR relatively other machining operations [8]. Due to high investment and machining costs, there is an economic need to operate machines as efficiently as possible in order to get the required benefits. The success of the machining operation depends on the selection of machining process parameters.These parameters play a major role such as ensure the excellence of product, decrease the machining cost and enhance productivity [9]. Identification of relationship between machining parameters and responses are essential for manufacturing industries [10].

The investigation of metal cutting focuses on the structures of tools, work materials, and machine parameter selection background and responses [11]. A significant improvement in process efficiency may be obtained by process parameter optimization that identified and determined the regions of critical process control factors leading to desire outputs or responses with acceptable variations ensuring a lower cost of manufacturing [12]. Surface finish and MRR correspond to the quality and productivity respectively [13]. So, the maximized productivity and better part quality is decided based on the machining parameter selection. In order to develop the quality of machining products, to trim down the machining costs and to enhance the machining effectiveness, it is very critical issue to choose optimum machining parameters in manufacturing industry where economy of machining operation plays a main role in competitiveness in the worldwide market [14]. So this work reviews the research work carried out on face milling modeling and optimization.

The main intend of this work is to create a model for face milling operation with spindle speed, feed rate and depth of cut as an input parameters and Surface Roughness & Material Removal Rate are output responses. Hence statistical tools such as Particle swarm optimization Techniques utilized by Bharathiraja et.al [15], Liang Gao et al. [16] and Baskar et al [17] , fuzzy logic Suresh Kumar et. al [18], artificial neural network techniques Francicus et.al [19] and Wang [20], , Taguchi techniques, Domnita et al [21], and Senthilkumaar et.al. [22], Design of Experiment (DoE) techniques used by Gianni Campatelli et al [23], Kannan et al [24 -27] and Sureshkumar et al [28] for an empirical model building. Various researchers used the non-traditional optimization techniques for identifying best parameter prediction Venkatta rao et al [29]. These parameters play an important role such as make sure the quality of product, reduce the machining cost and maximize the productivity.Surface roughness of the metal is a main influence on corrosion, nucleation of metastable pitting and pitting potential also [30]. RSM is one of the very important statistical tools for calculating the giving characteristics of independent variables. The main aim of this work is to building relationship between input and output parameters. Here, the input parameters are spindle speed; feed rate and depth of cut. The responses are MRR and SR. Finally, the verification tests are conducted for evaluating the performance of developed RSM models with experimental results. Varatharajulu et al. [32 – 34] studied the effect of exit burr height, exit burr thickness, roughness and roundness in Duplex 2205 using two different tool Solid Carbide and High Speed Steel, proposed non linear model for predicting the responses with good statistical values,

2. EXPERIMENTAL SETUP

The experiment conducted based on L 27 orthogonal array with respect to full factorial design. The three factors (Spindle speed, Feed rate and Depth of cut) and three levels were considered for eah factor. The considered levels were based on tool manufacturer recommendations and machine specifications.

The face milling operation were conducted on MCV - 400/400S CNC milling machine. The face milling operations were performed by using HSS cutter on Aluminium work pice materials. The chemical composition of aluminium work piece material shown in Table 1.

Table 1. Chemical composition of Aluminium

Aluminium							
Elements	Al	Si	Fe	Cu	Mn	Zn	Mg
%	97.59	0.60	0.27	0.11	0.45	0.11	0.62

The fig. 1 and fig. 2 show the aluminium work pice material and HSS milling cutter respectively. The cutter has 6 numbers of cutting edges with 40 mm diameter .The machining time is observed by the digital stop watch separately from the tool movement between home position and the work piece.

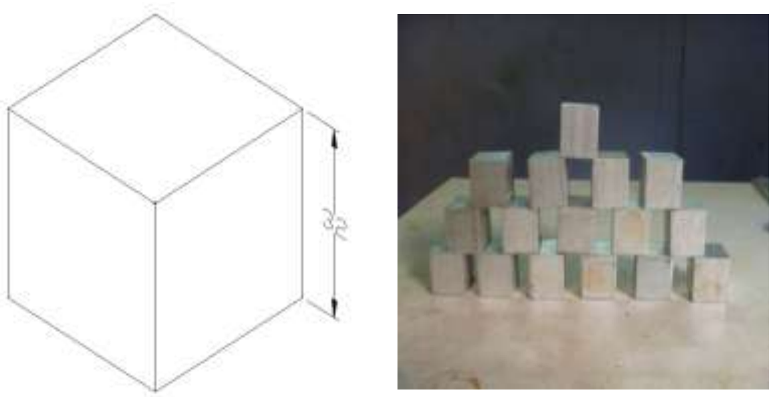

Fig 1: Aluminium work piece material

Fig 2: HSS milling cutter

Spindle speed, feed rate and depth are considered as input parameters for this experimental work. The Table 2 shows the range and levels of face milling input parameters which are used to carry out this work and these are considered based on machine and tool manufacturers recommendation.

Table 2. Ranges and levels of Input parameters

Independent variables	Unit	Ranges		
		Level I	Level II	Level III
Spindle speed	rpm	1100	1300	1500
Feed rate	mm /min	500	700	900
Depth of cut	mm	0.5	1	1.5

3. MATERIAL REMOVAL RATE (MRR)

The rate at which materials are removed from the aluminium work piece surface with help of face milling cutter. The amount of metal is removed from work piece per unit time is called as material removal rate. It is calculated by using equation (1) and the MRR is given in Table 6.

$$Q = WFD \qquad (1)$$

Where,

Q = Material removal rate (mm^3/min)

W = Width of cut (mm)

F = Table feed rate (mm/min)

D = Depth of cut (mm)

4. SURFACE ROUGHNESS (SR).

Increasing the productivity and the excellencies of the machined components are the major challenges of industry. Quality of machining can be refereed by surface roughness. Sukumar et al. [31] state that the higher the surface finish will be the higher quality. The actual surfaces show as absolutely straight lines, ideal circles, round holes, and other edges and surfaces that are geometrically ideal and determined by the manufacturing processes used to make it. Surfaces are very essential for various reasons such as aesthetic reasons, affect safety, friction and wear depend on surface characteristics, surfaces affect mechanical and physical properties, assembly of parts is affected by their surfaces, and smooth surfaces make better electrical contacts. Previously surface texture has been assessed by the opinion of the inspector either by eye or even fingernail. The evaluation was done by comparing the surface to be measured with standard surfaces A modern typical surface measuring instrument SJ -210 is used to measure the surface roughness of the machined aluminium work piece materials and it is tabulated in Table 6. SJ – 210 will consist of a stylus with a small tip (diamond) a gauge or transducer, a traverse datum and a processor. The surface is measured by moving the stylus across the surface.The surface roughness tester shown in fig.3 and its specifications are given in the Table3.

Fig 3: Surface roughness tester

Table 3. Specification of surface roughness tester

Make	MITUTOYO
Range	0 – 100 µm
Stylus type	SJ 210
Least count	0.1 µm

The main aim is to maximize the MRR subjected to preferred surface roughness value and it is based on the input parameters. This can be helped to the process planner for carried out the experiments without trial and error process. This can be reduced the cost of manufacturing.

5. RESPONSE SURFACE METHODOLOGY (RSM)

RSM is the combination of statistical and mathematical model technique, it propose the parameter influences and relation effect of process parameters on measured responses. This work considered the RSM technique for analyze the parameter role with ANOVA technique and construct the model with regression analysis. The ANOVA results and developed models performance evaluations are discussed in the following sections.

RSM is the combination of statistical and mathematical technique for making the relationship between dependent and independent variables. The interaction effects between the independent variables and dependent variables are identified with response surface plots. Similarly, this work uses the RSM technique for the study of parameter role with ANOVA technique and constructs the model with regression analysis. The following sections are discussed about ANOVA results and developed models performance evaluation. The main elements of ANOVA table are source of variance, sum of squares, degrees of freedom, mean square, F value, and the probability associated with the F value.

Table 4. ANOVA table for MRR

Source	Sum of Squares	Degrees of freedom	Mean Square	F Value	p-value Prob> F
Model	1.22E+09	8	1.52E+08	3928.744	< 0.0001
A-Spindle speed	50562	1	50562	1.30413	0.2865
B-Feed rate	3.05E+08	1	3.05E+08	7875.898	< 0.0001
C-Depth of cut	8.77E+08	1	8.77E+08	22629.61	< 0.0001
AB	18632.25	1	18632.25	0.480576	0.5078
AC	29412.25	1	29412.25	0.758621	0.4091
BC	35724529	1	35724529	921.4319	< 0.0001
A^2	14482.02	1	14482.02	0.37353	0.5580
B^2	2813.921	1	2813.921	0.072579	0.7944
Residual	310165.3	8	38770.67	3928.744	< 0.0001
Correlation Total	1.22E+09	16			

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The ANOVA Table 4 is critically analyzed about Aluminium with HSS cutter for identifying effects of machining parameters and interaction effects of machining parameters such as spindle speed, feed rate and depth of cut. The Model F-value of 3928.744 implies that the model is significant. There is only a 0.01% chance that a "Model F-Value" this large could occur due to noise. Values of "Prob> F" less than 0.0500 indicated that the model terms are significant. In this case B, C and BC are significant model terms. Values greater than 0.1000 shows that the model terms are not significant.

Table 5: ANOVA table for SR

Source	Sum of Squares	Degrees of freedom	Mean Square	F Value	p-value Prob> F
Model	4.580885	10	0.458089	111.9256	< 0.0001
A- Spindle speed	0.978121	1	0.978121	238.9861	< 0.0001
B-Feed rate	1.723296	1	1.723296	421.0561	< 0.0001
C- Depth of cut	0.975156	1	0.975156	238.2617	< 0.0001
AB	0.09	1	0.09	21.98986	0.0034
AC	0.355216	1	0.355216	86.79057	< 0.0001
BC	0.05313	1	0.05313	12.98141	0.0113
A^2	0.030439	1	0.030439	7.437333	0.0343
B^2	0.081176	1	0.081176	19.834	0.0043
A^2C	0.83916	1	0.83916	205.0335	< 0.0001
AB^2	0.150701	1	0.150701	36.82093	0.0009
Residual	0.024557	6	0.004093		
Correlation Total	4.605442	16			

The ANOVA Table 5 is fundamentally explains about Al with HSS cutter for identifying the process parameter effects. The Model F-value of 111.9256 indicated that the model is significant. There is only a 0.01% chance that a "Model F-Value" this large could occur due to noise. Values of "Prob > F" less than 0.0500 show that the model terms are significant. In this case A, B, C, AC, BC and A^2C are significant model terms.

6. Empirical Relationship between Independent and Dependent Variables

The regression models of MRR and SR are given in the equation (2) and (3) respectively. The MRR model has 0.99 R^2 value and SR model has 0.86 R^2 value. Therefore, these above two models are utilized to optimize the face machining parameters in face milling process. Based on response surface methodology, mathematical models of MRR and SR were constructed. This is one of the statistical procedures to make an empirical connection between dependent and independent variables. This work has created the mathematical models for MRR and SR. Feed rate, Spindle speed and depth of cut are considered as independent variables to create the models. . The ANOVA table is put together for identifying parameters part and interaction effects of independent variables on measured responses

Table 6 : Experimental Data

S. No.	Spindle Speed	Feed rate	Depth of Cut	MRR	SR
	rpm	mm/min	mm	mm^3/min	μm
1	1100	500	0.5	7920	3.994
2	1100	500	1	15585	3.353
3	1100	500	1.5	22815	2.387
4	1100	700	0.5	11088	4.629
5	1100	700	1	21875	4.527
6	1100	700	1.5	31941	3.725
7	1100	900	0.5	14252	4.008

8	1100	900	1	28044	4.056
9	1100	900	1.5	41121	3.905
10	1300	500	0.5	7920	2.593
11	1300	500	1	15580	2.846
12	1300	500	1.5	22808	3.811
13	1300	700	0.5	11085	3.309
14	1300	700	1	21784	3.714
15	1300	700	1.5	32015	3.592
16	1300	900	0.5	14333	3.677
17	1300	900	1	28134	4.019
18	1300	900	1.5	41175	4.434
19	1500	500	0.5	7918	2.549
20	1500	500	1	15885	2.613
21	1500	500	1.5	22890	3.271
22	1500	700	0.5	11071	3.044
23	1500	700	1	21854	3.672
24	1500	700	1.5	32267	3.332
25	1500	900	0.5	14256	4.025
26	1500	900	1	28071	3.916
27	1500	900	1.5	41135	3.926

From Table 6, the experimental data ranges are as follows for aluminium MRR calculated as 7918 mm^3/min and 41175 mm^3/min and SR measured are 2.387 µm and 4.629 µm.

Table 7: Model summary

Model	SD	R^2	Adj. R^2	Pre. R^2	Recommendation
Material removal rate					
Linear	1666.429	0.970382	0.963547	0.938022	
2FI	181.1702	0.999731	0.999569	0.998701	Suggested
Quadratic	46.35076	0.999988	0.999972	0.999803	
Cubic	0	1	1		Aliased
Surface roughness					
Linear	0.354074	0.646081	0.564407	0.266036	Suggested
2FI	0.336369	0.7543	0.60688	-0.23375	
Quadratic	0.378162	0.802616	0.503123	-2.47811	
Cubic	0.001342	0.999998	0.999994		Aliased

The Table 7 exactly denoted that the model summary of MRR and SR for aluminium work piece material with HSS cutter. Based on comparative study, the quadratic model has the higher R^2 value (0.999988 for MRR and 0.802616 for SR) than linear, 2FI and cubic models.The cubic model has R^2 value 1 for material removal rate and 0.999998 for SR, but it has lot of aliased terms so this model cannot be used for prediction. So the quadratic model is suitable for further data prediction and optimization of MRR and SR

$$MRR = 7658.574803 - 5.284686901 \times N - 3.82020676 \times f - 2633.787708 \times d + 0.002815782 \times N \times f + 2.083137105 \times N \times d + 30.1295475 \times f \times d \quad (2)$$

$$SR = 36.19881337 - 0.039624814 \times N - 0.004482266 \times f - 14.08411015 \times d + 3.91282 \times 10^{-6} \times N \times f + 0.009705139 \times N \times d + 0.009957901 \times f \times d + 1.01512 \times 10^{-5} \times N^2 + 2.50715E\text{-}07 \times f^2 + 0.300738801 \times d^2 - 7.07403 \times 10^{-5} \times N^2 \times f \times d \quad (3)$$

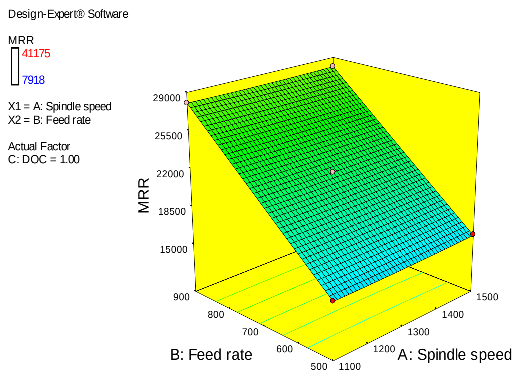

Fig 4. Material Removal Rate Vs Speed and Feed

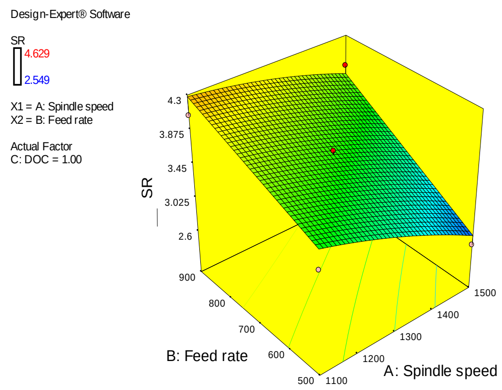

Fig 7. Surface Roughness Vs Spindle Speed and Feed

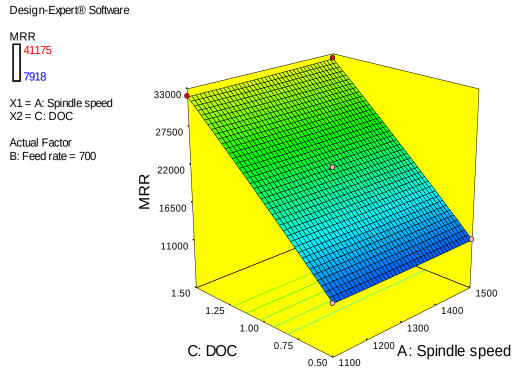

Fig 5. Material Removal Rate Vs Speed and Depth of cut

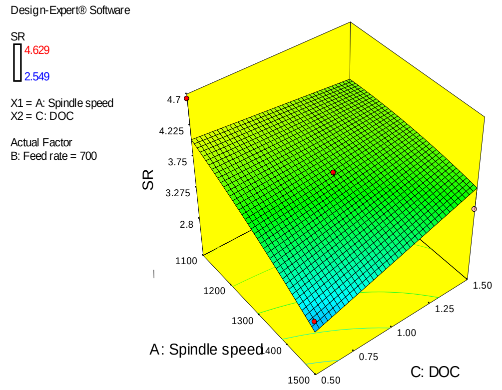

Fig 8. Surface Roughness Vs spindle Speed and Depth of cut

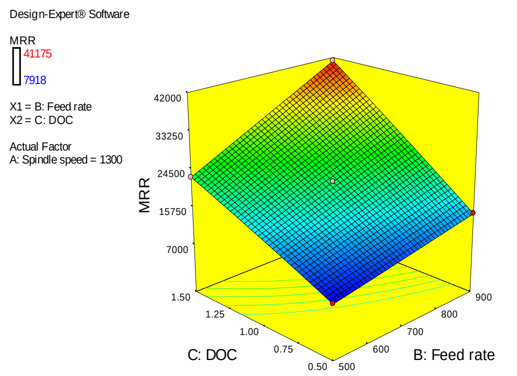

Fig 6. Material Removal Rate Vs Feed rate and Depth of cut

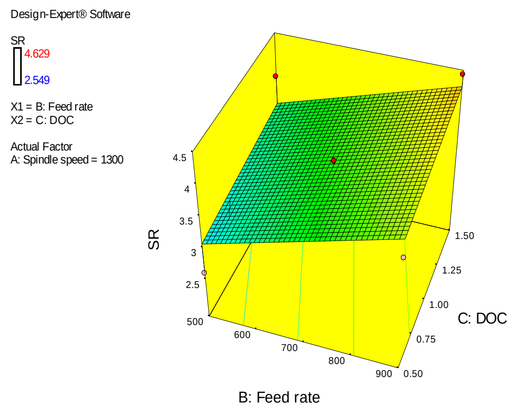

Fig. 9. Surface Roughness Vs Feed rate and Depth of cut

Validation prepared on the empirical model and the outcome of the validation confirms that the machining parameters of Design Expert give up the same MRR and close to SR value for aluminium. Still there is a slight difference in SR of experiment value from the value attain in empirical model. This difference can be sensible based on the effects of vibration, spindle run-out and material property of work piece. It is observed that, there is an increase in feed and depth of cut interaction increases the MRR as shown in fig 4, fig. 5 and fig. 6.There is no major contribution of interaction between speed & feed and speed & depth of cut on material removal rate.

From fig. 7, fig. 8 and fig. 7, it is evident that, enhance in feed and depth of cut interface to increases the roughness at a few level. Increase in speed & feed and speed & depth of cut interface trim down the roughness

Table 8 : Performance Evaluations at Developed Model with Experimental Values

Serial number of Experiment	Material Removal Rate (MRR)			Surface Roughness (SR)		
	Exp. Value of MRR	Predicted MRR	% of Deviation	Exp. Value of SR	Predicted SR	% of Deviation
	mm^3	mm^3		μm	μm	
1	7920	7856	0.8066	3.994	3.916	1.960
2	15585	15614	-0.1858	3.353	3.294	1.768
3	22815	22755	0.2648	2.387	2.445	-2.426
4	11088	11097	-0.0805	4.629	4.628	0.030
5	21875	21832	0.1972	4.527	4.292	5.195
6	31941	31950	-0.0269	3.725	3.729	-0.111
7	14252	14330	-0.5510	4.008	4.168	-3.985
8	28044	28042	0.0069	4.056	4.118	-1.530
9	41121	41137	-0.0386	3.905	3.842	1.624
10	7920	7891	0.3640	2.593	2.655	-2.393
11	15580	15678	-0.6265	2.846	3.144	-10.455
12	22808	22847	-0.1725	3.811	3.752	1.556
13	11085	11090	-0.0517	3.309	3.275	1.041
14	21784	21854	-0.3203	3.714	3.708	0.149
15	32015	32000	0.0450	3.592	4.262	-18.654
16	14333	14282	0.3553	3.677	3.618	1.612
17	28134	28022	0.3973	4.019	3.997	0.546
18	41175	41146	0.0713	4.434	4.496	-1.399
19	7918	7984	-0.8402	2.549	2.245	11.938
20	15885	15799	0.5410	2.613	2.554	2.269
21	22890	22997	-0.4669	3.271	3.329	-1.770
22	11071	11141	-0.6398	3.044	3.043	0.045
23	21854	21933	-0.3636	3.672	2.956	19.491
24	32267	32108	0.4900	3.332	3.336	-0.125
25	14256	14291	-0.2449	4.025	4.460	-10.800
26	28071	28060	0.0386	3.916	3.978	-1.585
27	41135	41212	-0.1889	3.926	3.963	-0.931
Overall percentage of deviation			**-0.045**			**-0.257**

The table 8 shows the percentage of deviation between predicted values and experimental values. The fig 10 & fig 11 show the factual and foretell comparison plot for MRR and SR respectively. The actual and predicted values are very closer to each other. The differences between experimental value and predicted values are very minimum. So, this work further extended for optimization by using GA.

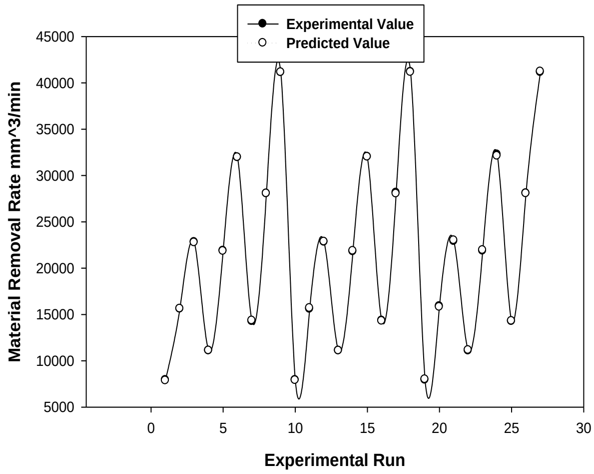

Fig. 10. ***Experimental and Predicted MRR***

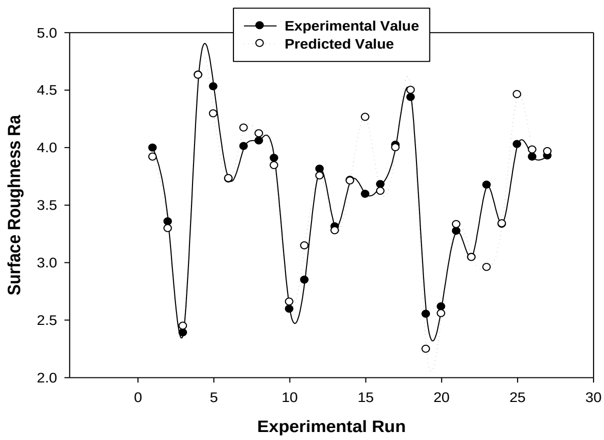

Fig. 11. ***Experimental and Predicted SR***

7. Genetic Algorithm

In the natural selection processes, GA plays a major role to select the best parameter value for relevant area. GA has significant performance on combinatorial optimization problems; a population of candidate solutions is maintained. The initial population, candidate solutions are randomly generated. New solutions are generated by reproduction, cross over and mutation.

7.1 Combined Objective Function

Manufacturers expected to maximize the material removal rate and also minimize the surface roughness of the work piece. The needs of the manufacturer, it is required to formulate the new objective function which consists of material removal rate and surface roughness. The Combined Objective Function (COF) is based on the empirical equations of surface roughness and material removal rate. The COF is given below in equation (4) & (5)

$$\text{Min COF} = \frac{0.5\times \text{SR}}{\text{Min. SR (Expt .Value)}} - \frac{0.5\times\text{MRR}}{\text{Max. MRR (Expt. Value)}} \qquad (4)$$

$$\text{Min COF} = \frac{0.5\times(\text{Eq. 3})}{\text{Min. SR (Expt. Value)}} - \frac{0.5\times(\text{Eq. 2})}{\text{Max. MRR (Expt. Value)}} \qquad (5)$$

7.2 Computational Result of GA

The Genetic Algorithm (GA) concept is developed with help of c++ program. The GA input factors are the crossover probability and it is 0.8, the population range is 100, probability of mutation is 0.1, and the number of iterations measured for this work is 500 generations. From the fig 12, the output of GA obtained for combined objective function of MRR is 17497.46 mm^3/ min and SR is 4.31µm. The best value is achieved at 212th iteration. The corresponding best parameter values are shown in Table 9.

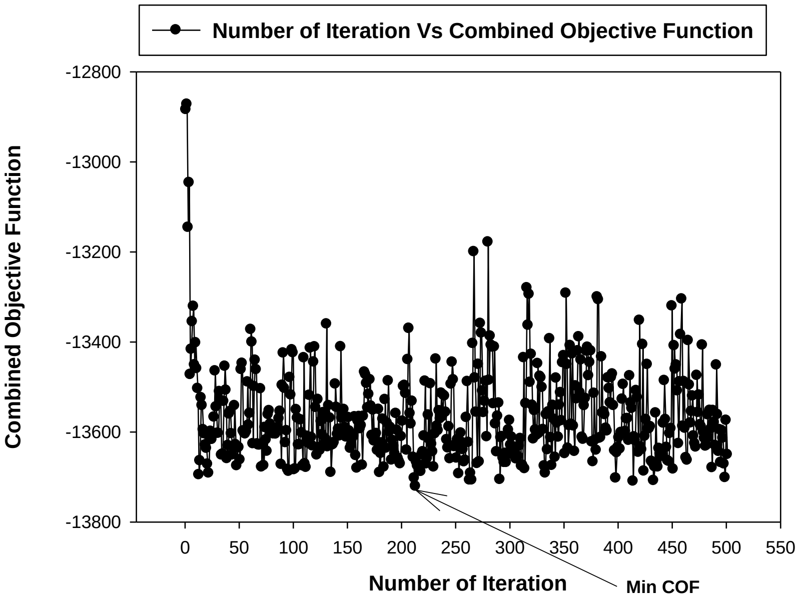

Fig. 12. Results of Genetic Algorithm

Table 9: Best results from GA for Al with HSS cutter

S. No.	Parameters		MRR (mm^3/min)	SR (µm)	Min COF
1	Spindle Speed (rpm)	1499.71	17497.46	4.31	-13721.05
2	Feed rate (mm/min)	899.90			
3	Depth of cut (mm)	0.61			

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8. Conclusions

Based on the experimental and theoretical work with the help of Response surface methodology & Genetic algorithm the following conclusions were observed . This shows the reliable impact on the models for face milling of Aluminium.

- The minimum and maximum value of MRR (7918 and 41135 mm^3/min) and SR (2.387 and 4.629 µm) were the outcome of Aluminium material face milling with HSS cutter.
- The optimal value for Aluminium with HSS cutter are Spindle speed 1499.71rpm, feed rate 898.90 mm/min and depth of cut 0.61mm
- Combination of RSM and GA proves to be the effective tool for optimization of face milling parameters
- The performance analysis on developed empirical models shows less variation with experimental results. The overall precision rate for present approach of SR and MRR were found to be 80% and 99% respectively
- The developed empirical models for MRR and SR can be developed to achieve the greatest optimal machining parameters for face milling of aluminium by HSS cutter.
- It has been established that combined objective function for SR and MRR models make clear to an efficient ways to obtained the best results for incompatible solutions
- Further, this work can be extended to other type of milling operations such as pocket milling, end milling to find the best optimal parameters.

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