Modeling and Optimization of Face Milling Operation Based on Response Surface Methodology and Genetic Algorithm

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Abstract:- **Materials are manufactured from casting, forging and extrusion processes have higher typical dimension tolerences due to its producing ability. So machining processes were introduced for close tolerence asssembly and improve the product working efficiencies. In response, now a day's lot of machining processes are available such as turning, milling, drilling and grinding to overcome these problems. Milling operation is playing vital role on making the components with high accuracy and higher productivity. Subsequently, face milling operation is utilized for planning the surface of work material with improved surface texture.It is one of the important milling processes to achieve high flatness and low roughness. The work enlights the parameters influence on Material Removal Rate (MRR) and Surface Roughness (SR) in aluminium as a work piece material. In fact, aluminium alloy has the most significant in automobile and automation industries because of its inherent properties such as low weight to strength ratio. The selection of milling parameters such as spindle speed, feed rate and depth of cut are essential for improving the productivity and part quality.This work formulates the relationship between input and response variables for improving the face milling performances. The Response Surface Methodology (RSM) is utilized for making the relationship between independent and dependent variables. Finally, the selection of the best parameter is important to the manufacturing industries in order to improve the productivity and product quality through scientific approach. The performance of RSM models show the developed empirical relationship and it has the best agreement with experimental results. The Genetic Algorithm (GA) is used to select the optimal machining parameters.**

Keywords: Face milling, Material Removal Rate, Surface Roughness, Genetic Algorithm.

I. INTRODUCTION

Machining operation is one of the important processes, where the tight tolerance and assembly requirements in structures and machine assembly. Most of the machine components are finished by milling operation for higher dimensional accuracy. In milling, various cutting approaches such as slot milling, end milling etc., are considered to accomplish the assembling task due to its position, location and orientation of work piece for assembling scenario. Identification of relationship between machining parameters and responses are important for manufacturing industries [1]. Therefore, the main aim of this work is to model and optimize the face milling operation. Now-a-day's statistical tools, fuzzy logic, artificial neural network techniques and non-traditional optimization techniques are used for modeling and optimization respectively. Subsequently, mechanistic models are not suitable for newer materials due to experimental risks such as machining condition, hardness, surface roughness etc. So the empirical models are needed for every individual machine for its specific performance and its specifications. Simultaneously, the non-traditional techniques are significant for global selection rather than local selection that succeeded by the traditional techniques. So, new trends are required for manufacturing engineering to evaluate the process characteristics in machining. Many researchers were used the trial and error experiments and it was tedious, time consuming and more expensive methods [13]. In response, there is an economic need to operate machines as efficiently as possible in order to obtain the required pay back. And the success of the machining operation depends on the selection of machining process parameters. These parameters play a significant role such as ensure the quality of product, reduce the machining cost and increase productivity [2].

Milling is one of the machining processes, which producing flat, contoured and helical surfaces by means of multipoint rotating cutting tool called milling cutter. The work piece is clamped on the work table, and is given a linear feed against the rotating cutter. The speed of cutting tool and the rate of work piece travels are based on the workpiece and tool materials. Similarly two or more cutting edges in milling cutter provided higher material removal rate rather than other machining operations [3].

Now a day's non - traditional optimization techniques are popular for optimization of machining parameters. In sense, Tolouei-Rad and Bidhendi [1] used the method of feasible direction and considered maximization of profit rate as an objective function in milling operation. The feasible solutions are afforded the local minimum of the problem. However, this local minimum need not be the global one unless the problem is convex programming problem. Venkata Rao and Pawar [4] used three non-traditional optimization algorithms namely, artificial bee colony, particle swarm optimization and simulated annealing for multi-pass milling process parameter optimization. Lu, Chang, Hwang and Chung [5] used grey relational grade as performance index is specially adopted to determine the optimal combination of cutting parameters. Franci Cus and Uros Zuperl [6] used neural network-based approach to complex optimization of cutting parameters. Proposed approach has advantages than interactive approaches especially for job-shop production systems where product mix is diverse and dynamic. Baskar et al [7, 14] considered a specific case in milling operation and solved the same by using three different non-traditional optimization techniques comprising a genetic algorithm, local hill climbing and memetic algorithm. Shin and Joo [8] used the dynamic programming optimization method for milling process parameter optimization. However, for the optimization problem involving large amount of independent parameters with a wide range of values such as the cutting parameters in milling operation, the use of dynamic programming is limited. Wang [9] used a neural network based approach to optimize milling process parameters.

However, optimization by using neural networks may often ends in local minima or fails to converge on a result. Optimization model developed in their work was non-convex. Sonmez et al. [10] studied multi-pass milling operation based on the maximum production rate criterion and used an algorithm adopted from the study of Agapiou [11] which was presented for the multi-pass turning operations. Although the results showed significant improvement over handbook recommendations, the optimization techniques used in their work (dynamic programming and using geometric programming) either tend to result in local minimum or take a long time to converge on a reasonable result. Where as many researchers were utilized Taguchi technique for identifying the sound noise ratio of process parameters and optimization of parameters. Ultimately, their work is not concentrated on optimization with Non-traditional optimization techniques [15 – 17]. This work strives to achieve the best parameters selection with combination of RSM and GA. The efficient utilization of machine tools has been a problem for manufacturing firms for a long time. The investment of the machines and fulfilling the customer requirements are great importance in the manufacturing processes. A number of researchers have dealt with the optimization of machining variables considering turning operations [18 -19]. Multi point machining has received very diminutive attention for optimizing the machining variables. Wang and Hsu [20] studied the surface roughness in aluminium using milling processes and the sequential neural network approximation method was used to find the optimal machining parameters to maximize the MRR for the desired surface roughness. Wang and Jawahir [21] presented genetic algorithm for the selection of cutting conditions in single pass milling operation and also case studies presented for the determination of cutting condition in face and end milling operation. Vijayakumar et.al,[23] studied surface roughness in aluminum alloy using end milling process and GA method was used to find the optimal machining parameter for desired surface roughness.

However many researchers were examined the fuzzy logic [12], Taguchi technique and grey relational techniques to optimize the process parameters on face milling operation. Very few researchers concentrated on RSM technique for machining problems. RSM is one of the important statistical tools for calculate the performance characteristics of independent variables. Simultaneously, lot of researchers were examined the GA and it is one of the best optimization techniques for global optimization. So, the main aim of this work is to combine the RSM and GA for modeling and to optimize the variables in face milling operation.

II. EXPERIMENTAL SETUP

The experiments were conducted based on L 27 orthogonal array with respect to full factorial design. The three factors and each three levels with two replicates were considered based on machine tool specifications and tool manufacturer recommendations.

A. Machine Specifications

The experiments were conducted on AKSARA VF 30 CNC machining center as shown in fig 1.

The specification of milling machine is given in Table I.

Fig. 1. CNC Milling Machine

TABLE I
Specification of AKSARA VF30 CNC Machining Center

Travel x-axis y axis z axis	 800 mm 350 mm 480 mm
Table dimension Length Width	 1000 mm 350 mm
Spindle speed Max. motor rating	0 – 2000 rpm 5 Kw
Feed rates max. rapids Max .cutting	10 m/min 5 m/min
Tool Type Max. tool diameter Max. tool weight	 BT40 150 mm 10 kg
Accuracy Positioning Repeatability	 +/- 0.0051 mm +/-0.0025 mm
General Power	 10 kW

B. Work piece

Aluminium is identified for conducting experiments, as they are the most commonly used material in manufacturing industry. Size of the work piece material is 32 mm cube as shown in figure. 2

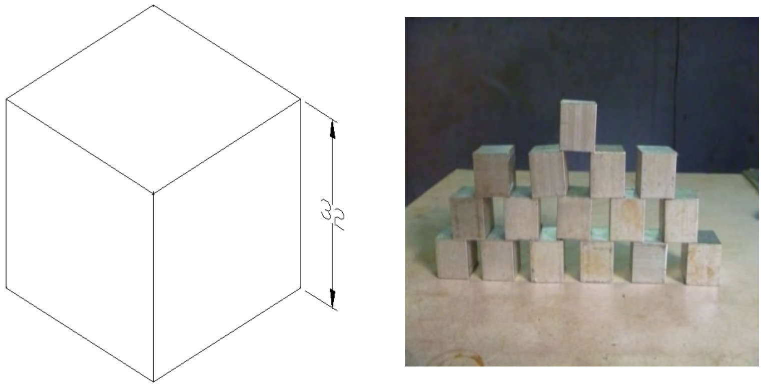

Fig. 2. Aluminium Work piece Material

C. Tool and Insert

The tool diameter is a key factor while calculating the material removal rate. The diameter of tool is considered as 50 mm for this experiment. Tungsten carbide inserts are used for this experimental work and the part name of this insert is

APMT – 16, where

A – Type IV Non – equilateral and non – equiangular inserts, Parallelogram shape, 85^0 nose angle,

P – Relief angle 11^0,

M – Tolerance (Corner point (m) ±0.08 to ±0.20, Thickness ±0.13, Inscribed circle ±0.05 to ±0.15),

T –With hole Shape of hole – Partly cylindrical hole, 40^0 – 60^0 counter sink on one side only,

Chip breaker single sided,

16 – Width of the tool.

D. Independent Variables

The machining parameters are depending on the parameters such as speed, feed and depth of cut. The Table II shows the range and levels of machining parameters considered for experimental work

TABLE II
Ranges and Levels of Input Parameters

Independent variables	**Unit**	**Ranges**		
		Level I	**Level II**	**Level III**
Speed	rpm	1000	1400	2000
Feed	mm /min	1000	1100	1600
Depth of cut	mm	0.5	1	1.5

E. Measurements of Responses

The machining time is observed from the program running time to complete the face milling operation on work piece material. The surface roughness tester SJ-210 as shown in figure 3 is used to measure the surface roughness of the machined work piece. The surface roughness tester and its specifications are shown in figure 3 and the Table III respectively.

Fig. 3. Surface Roughness Tester

TABLE III
Specification of surface roughness tester

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

The objective is to maximize the MRR subjected to desired surface roughness value and it depends on the input parameters. This can be help to the process planner for conducting experiments without trial and error method. This can reduce the cost of the experiments.

1) Material Removal Rate (MRR)

The rate at which material is removed from the blank by milling process is termed as material removal rate. And it is usually expressed in cubic millimeter/minute. It is calculated by using the equation (1) and the same is presented in Table IV.

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

Where, Q = Material removal rate (mm^3/min)
W = Width of cut (mm)
F = Table feed (mm/min)
D = Depth of cut (mm)
V = Spindle speed (rpm)

2) Surface Roughness (SR)

The surface roughness tester SJ - 210 is used to measure the surface roughness of the machined work piece and the measured surface roughness value is tabulated in Table IV.

TABLE IV
Experimental Data

S. No.	Spindle Speed	Feed	Depth of Cut	Average MRR	Average Roughness
	rpm	*mm/min*	*mm*	*mm^3/min*	*μm*
1	2000	1600	0.5	25408	3.341
2	2000	1600	1	48848	3.009
3	2000	1600	1.5	75552	2.524
4	2000	1100	0.5	16566	1.563
5	2000	1100	1	35123	2.527
6	2000	1100	1.5	50506.5	2.988
7	2000	800	0.5	12716	1.971
8	2000	800	1	24680	2.050
9	2000	800	1.5	37428	1.696
10	1400	1600	0.5	23996	1.374
11	1400	1600	1	50496	1.253
12	1400	1600	1.5	72288	1.388
13	1400	1100	0.5	17424	2.118
14	1400	1100	1	33698.5	2.055
15	1400	1100	1.5	51859.5	2.516
16	1400	800	0.5	12038	2.774
17	1400	800	1	25184	2.632
18	1400	800	1.5	36120	2.458
19	1000	1600	0.5	25312	8.825
20	*1000*	*1600*	*1*	*48976*	*8.553*
21	1000	1600	1.5	75000	8.363
22	1000	1100	0.5	16585.25	8.501
23	1000	1100	1	35376	5.555
24	1000	1100	1.5	49013.25	5.267
25	1000	800	0.5	12660	3.185
26	1000	800	1	24588	2.940
27	1000	800	1.5	37548	4.100

F. Response Surface Methodology (RSM)

RSM is the combination of statistical and mathematical model technique, that propose the parameter influences and interaction effect of process parameters on considered responses. This work utilizes the RSM technique for analyze the parameter contribution with ANOVA technique and build the model with regression analysis. The following sections are discussed about ANOVA results and developed models performance evaluation.

TABLE V
ANOVA Table for Material Removal Rate

Source	Sum of Squares	Degrees of freedom	Mean Square	F Value	p-value Prob > F
Model	5130968130	6	855161354.9	760.6435567	< 0.0001
A-Speed	73698.67964	1	73698.67964	0.065553039	0.8031
B-Feed	1528161042	1	1528161042	1359.259096	< 0.0001
C-DOC	3092137406	1	3092137406	2750.37498	< 0.0001
AB	2077537.487	1	2077537.487	1.847915009	0.2039
AC	1186412.286	1	1186412.286	1.055282557	0.3285
BC	214399934.1	1	214399934.1	190.7031082	< 0.0001
Residual	11242603.02	10	1124260.302		
Correlation Total	5142210733	16			

The Table V shows the MRR ANOVA table. The Model F - Value of 760.64 implies that the model is significant. Even though the experiments are conducted with 99% confidence level and there is a large F- value is obtained in the developed mathematical model due to the noise. The Values of “Prob > F” is less than 0.0500 indicate that model terms are significant. Based on the ANOVA table, B, C and BC are significant. The values are greater than 0.1000 indicate that the model terms are not significant.

TABLE VI
ANOVA Table for Surface Roughness

Source	Sum of Squares	Degrees of freedom	Mean Square	F Value	p-value Prob > F
Model	39.3863831	10	3.938638315	1.73085698	0.2591
A-Speed	19.3605605	1	19.3605605	8.5081083	0.0267
B-Feed	2.75149456	1	2.751494563	1.20915992	0.3136
C-DOC	0.15279177	1	0.152791766	0.06714521	0.8042
AB	2.30980149	1	2.309801486	1.01505539	0.3526
AC	0.34386036	1	0.343860359	0.15111139	0.7109
BC	0.09893525	1	0.098935252	0.04347766	0.8417
A^2	15.8276765	1	15.82767653	6.95556237	0.0387
B^2	0.00475139	1	0.004751387	0.00208802	0.9650
C^2	0.01422297	1	0.014222972	0.00625037	0.9396
ABC	1.1246624	1	1.124662403	0.49423928	0.5084
Residual	13.6532539	6	2.275542319		
Correlation Total	53.0396371	16			

The Table VI shows the surface roughness ANOVA table. The “Model F- Value” of 1.73 implies that the model is not significant relative to the noise. The experiments are conducted with 74.09% confidence level and large F- value is obtained in the developed mathematical model. The values of “Prob > F” is less than 0.0500 indicate that the model terms are significant. In this case, A and A^2 are significant model. The values are greater than 0.1000 and it indicates that the model terms are not significant.

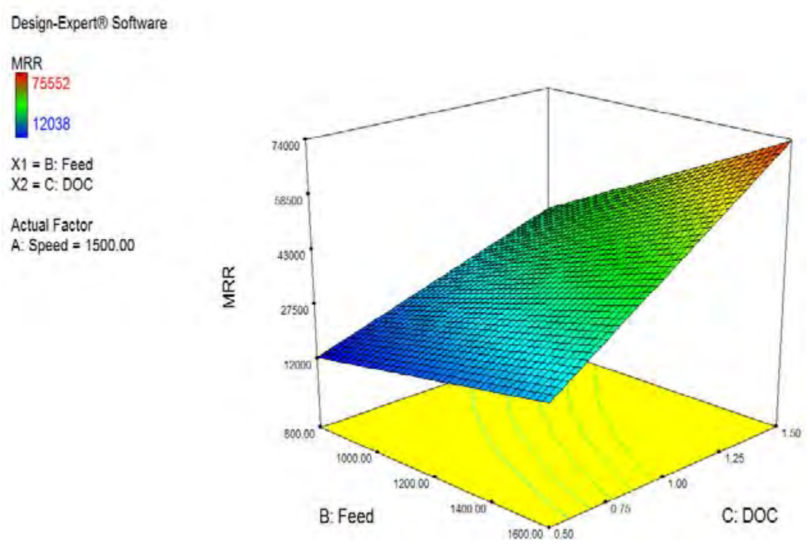

Fig. 4. Material Removal Rate Vs Feed and Depth of Cut

It is observed that there is an increase in feed and depth of cut interaction increases the MRR as shown in figure 4. There is no significant contribution of interaction in speed & feed and speed & depth of cut on MRR. From figure 4, it is observed that increase in feed and depth of cut interaction slightly increases the roughness. Increase in speed & feed and speed and depth of cut interaction decreases the roughness.

1) Empirical Relationship Between Independent and Dependent Variables

The regression models of MRR and surface roughness are given in equation (2) and (3) respectively. The MRR model has 0.99 R squared value and surface roughness model has 0.75 R squared value. In that surface roughness model is the weakest model from the experimental data. However, these two models are used to optimize the machining parameters in face milling operation.

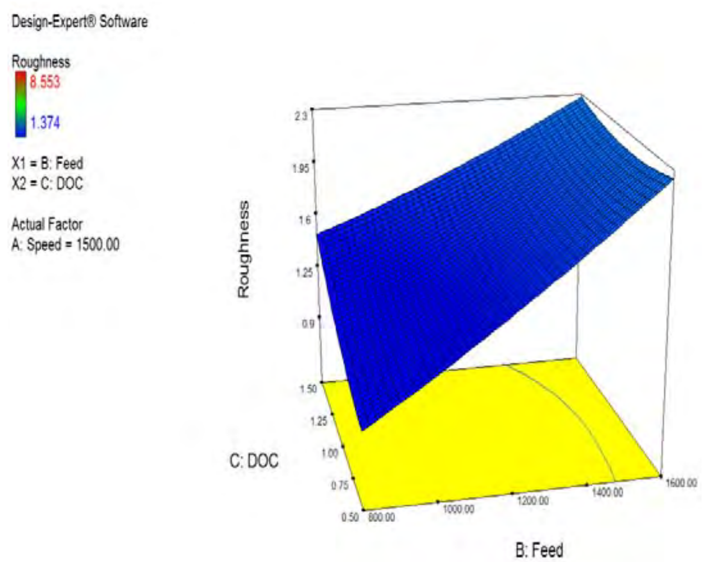

Fig. 5. Surface Roughness Vs Feed and Depth of Cut

2) Performance Evaluation of Developed Empirical Model

The relationship between dependent and independent variables required a statement of statistical model [12]. In the response, the mathematical models were developed based on response surface methodology. This is one of the statistical techniques to make an empirical relationship between dependent and independent variables. This work has developed the mathematical models for MRR and surface roughness. The independent variables considered to generate the models are spindle speed, feed rate and depth of cut. The ANOVA table is formulated for identifying parameters contribution and interaction effects of independent variables on considered responses.

$$MRR = 7658.574803 - 5.284686901 * V - 3.82020676 * F - 2633.787708 * D + 0.002815782 * V * F + 2.083137105 * V * D + 30.1295475 * F * D \quad (2)$$

$$SR = 36.1988134 - 0.0396248 * V - 0.0044823 * F - 14.08411 * D + 3.9128E\text{-}06 * V * F + 0.00970514 * V * D + 0.0099579 * F * D + 1.0151E\text{-}05 * V^2 + 2.5071E - 07 * F^2 + 0.3007388 * D^2 - 7.074E - 06 * V * F * D \quad (3)$$

Validation made on the empirical model and the results of the validation proved that the machining parameters of Design Expert could yield the same material removal rate and near surface roughness value for a given component. Even though there is slight deviation in surface roughness of experiment value from the value obtained in Design Expert formulae, the deviation can be justified based on the effects of vibration, spindle run-out and work piece material property.

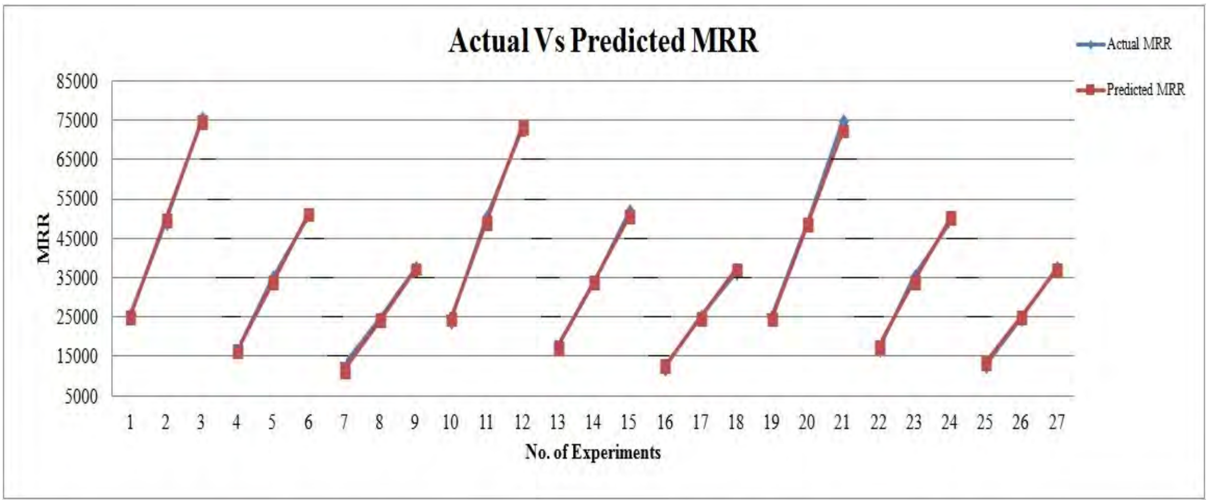

Fig. 6. Actual Vs Predicted MRR

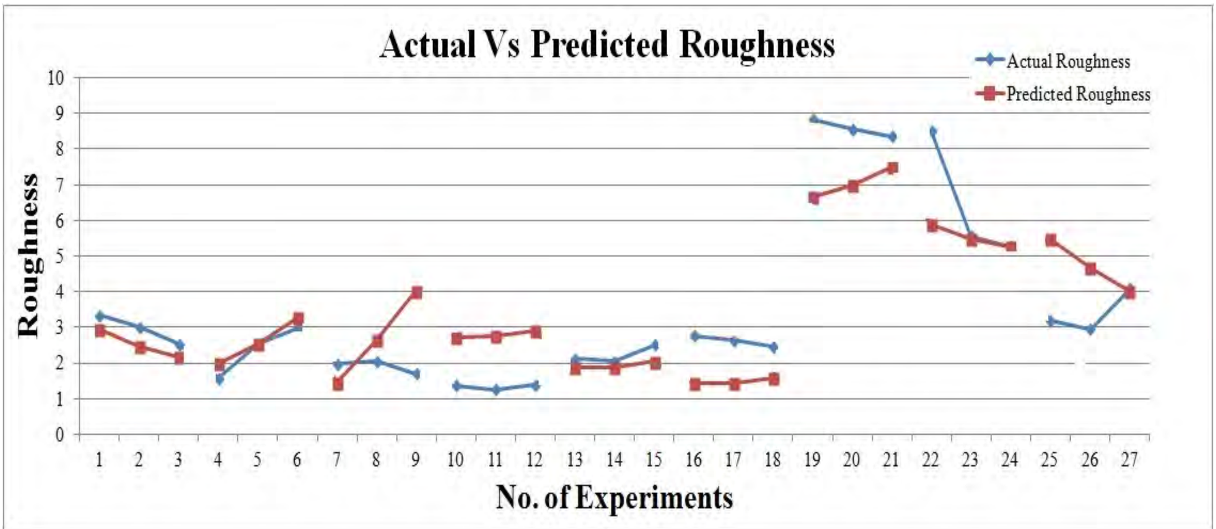

Fig. 7. Actual Vs Predicted Roughness

The figures 6 & 7 are show the actual and predicted comparison plot for MRR and Surface Roughness respectively. The actual values are very close to predicted values. The Table VII shows the % of deviation between predicted values and experimental values. The deviations between experimental and predicted values are smaller so this work extended for optimization.

TABLE VII
Performance Evaluations at Developed Model with Experimental Values

S. No.	Spindle Speed (rpm)	Feed (mm/min)	Depth of cut (mm)	MRR (mm^3/min)			Surface roughness (μm)		
				Experimental value	Predicted value	% of deviation	Experimental value	Predicted value	% of deviation
1	2000	1600	0.5	25408	24857.25309	2.168	3.341	2.93154	12.242
2	2000	1600	1	48848	49727.13435	-1.8	3.009	2.46806	17.977
3	2000	1600	1.5	75552	74597.0156	1.264	2.524	2.15494	14.605
4	2000	1100	0.5	16566	16419.18783	0.886	1.563	1.96893	-26.012
5	2000	1100	1	35123	33756.68221	3.89	2.527	2.55299	-1.048
6	2000	1100	1.5	50506.5	51094.17659	-1.164	2.988	3.28741	-10.039
7	2000	800	0.5	12716	11356.34867	10.692	1.971	1.45154	26.355
8	2000	800	1	24680	24174.41093	2.049	2.050	2.66411	-29.988
9	2000	800	1.5	37428	36992.47318	1.164	1.696	4.02706	-137.515
10	1400	1600	0.5	23996	24699.97361	-2.934	1.374	2.72557	-98.368
11	1400	1600	1	50496	48944.91373	3.072	1.253	2.74608	-119.248
12	1400	1600	1.5	72288	73189.85385	-1.248	1.388	2.91696	-110.156
13	1400	1100	0.5	17424	17106.64287	1.821	2.118	1.8757	11.44
14	1400	1100	1	33698.5	33819.19612	-0.358	2.055	1.88264	8.365
15	1400	1100	1.5	51859.5	50531.74936	2.56	2.516	2.03995	18.921
16	1400	800	0.5	12038	12550.64443	-4.259	2.774	1.42595	48.596
17	1400	800	1	25184	24743.76555	1.748	2.632	1.42475	45.868
18	1400	800	1.5	36120	36936.88667	-2.262	2.458	1.57392	35.954
19	1000	1600	0.5	25312	24595.12061	2.832	8.825	6.64876	24.656
20	1000	1600	1	48976	48423.43331	1.128	8.553	6.99193	18.247
21	1000	1600	1.5	75000	72251.74601	3.664	8.363	7.48546	10.488
22	1000	1100	0.5	16585.25	17564.94623	-5.907	8.501	5.87405	30.902
23	1000	1100	1	35376	33860.87206	4.283	5.555	5.49625	1.049
24	1000	1100	1.5	49013.25	50156.79788	-2.333	5.267	5.26882	-0.035
25	1000	800	0.5	12660	13346.84161	-5.425	3.185	5.46939	-71.723
26	1000	800	1	24588	25123.33531	-2.177	2.940	4.65901	-58.47
27	1000	800	1.5	37548	36899.82901	1.726	4.100	3.999	2.452
Overall Percentage of deviation						0.559			-12.388

III. GENETIC ALGORITHM

GA is one of the natural selection processes to select the best parameter value for respective 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.

A. Reproduction

Reproduction is typically the first operation, realistic on a population. Reproduction decides on good strings in a population and outlines a mating pool.

B. Crossover

In crossover, new strings are generated by replacing information between strings of the mating pool. In fact strings are chosen from the mating pool and some portions of the strings are swapped between the strings based on the cross over probability.

C. Mutation

The mutation operator modifies 1 or 0 and vice versa with a small mutation probability, the need for mutation is to create a point in the neighbour of the current point, thereby achieving a local search around the current solution. The mutation is also used to maintain diversity in the population.

D. Algorithm

Step 1: Select a coding to stand for problem parameters [22], a selection operator, a crossover and a mutation operator. Choose population size *n*, crossover probability *p*c. Initially a random population of string of size is 1. Choose a maximum allowable number *t* max. Set *t*=0.

Step 2: Estimate each string in the population.

Step 3: If *t* > *t* max (or) other termination criteria is satisfied, terminate.

Step 4: Execute reproduction on the population.

Step 5: Carry out crossover on random pairs of string.

Step 6: Achieve bit-wise mutation.

Step 7: Estimate string in the new population. Set *t* = *t* + 1 and

go to Step 3.

End.

E. *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 that it is necessitate formulating the new objective function which consists of MRR and Surface roughness. The Combined Objective Function (COF) is formulated based on the empirical equations of surface roughness and MRR. The COF is given below in equation (4)

$$Min\ COF = 0.5\ SR - 0.5\ MRR \qquad (4)$$

F. *Computational Results of GA*

The GA concept is developed with c++ program. The GA input parameters are the crossover probability is 0.8, mutation probability is 0.1, the population size is 100 and the number of iterations considered for this work is 500 generations. Finally, the GA output is shown in figure 8 for combined objective function of MRR and surface roughness. The optimal value is obtained at 324th iteration. The corresponding best parameter values are shown in Table VIII.

TABLE VIII
Best Result from Genetic Algorithm

Iteration (no.)	Speed (rpm)	Feed (mm/min)	DOC (mm)	Min COF	MRR (mm^3/min)	SR (µm)
324	**1917.65**	1600	1.49	-74118	88580.19	1.8

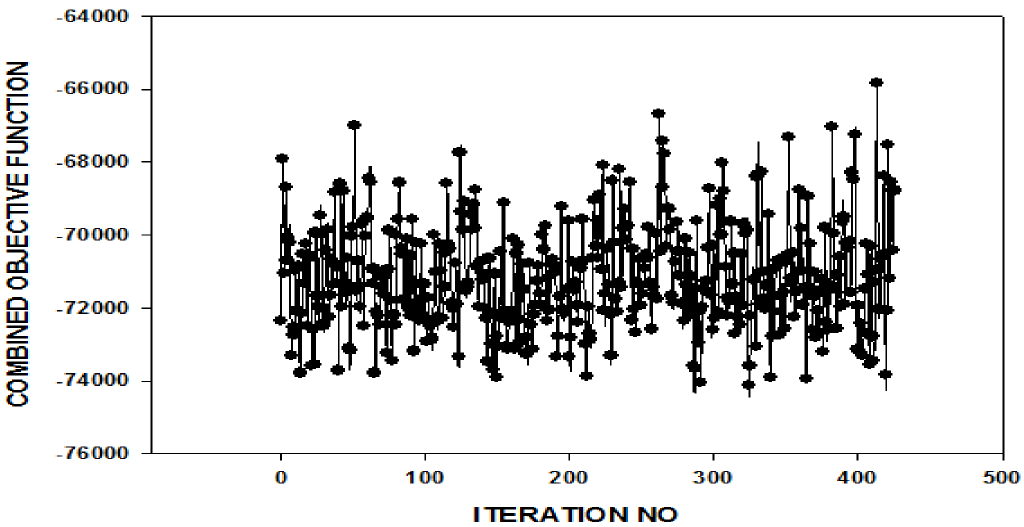

Fig. 8. Results of Genetic Algorithm

IV. CONCLUSIONS

This work integrates the Response Surface Methodology with Genetic Algorithm for face milling operation. Based on the experimental and theoretical work, the following conclusions were arrived.

- The hybridization of RSM and GA is an effective methodology for optimization of machining parameters in face milling operation.
- The performance test of developed models has less percentage of deviation with experimental results. The overall accuracy rate of present approach for MRR and surface roughness are 99% and 74% respectively.
- So the developed empirical models with RSM for MRR and surface roughness of aluminum face milling using tungsten carbide can be used to achieve optimal machining parameters.
- For better surface finish, the maximum level of cutting speed with minimum level of feed and depth of cut is recommended.
- The Surface Roughness and Material Removal Rate models are combined for attaining combined objective function. It is effective for obtain the best results of conflicting objectives.
- Finally the GA is utilized for getting best machining parameters. This work can be extended to other type of milling operations such as end milling, pocket milling etc.

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