SELECTION OF MACHINING PARAMETERS IN FACE MILLING OPERATIONS FOR COPPER WORK PIECE MATERIAL USING RESPONSE SURFACE METHODOLOGY AND GENETIC ALGORITHM

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Abstract

Face milling operation is one of the essential milling processes and it is used for planning the topsurface of the component to achieve high accuracy with low roughness. The work enlights the parameters influence on Material Removal Rate (MRR) and Surface Roughness (SR) in copper as a work piece material. Conseuently the selection of milling parameters such as spindle speed, feed rate and depth of cut are importnat for improving the productivity and part quality. This work formulates the relationship between input and response variables for improving the face milling operation. The Response Surface Methodology (RSM) is used for making the relationship between independent and dependent variables. The performance of RSM models show the developed empirical relationship and it has the best agreement with experimental results. The Genetic Algorithm (GA) is utilized for select the optimal machining parameters.

Keywords:Material Removal Rate, Surface Roughness, Response Surface Methodology, Genetic Algorithm.

1 Introduction

Machining operation is one of the important processes, where the high tolerance and assembly requirements in structures and machine assembly. In general, the machine components are finished by milling operation for higher dimensional accuracy. In milling, various cutting methods such as slot milling, end milling etc., are considered to achieve the assembling task due to its location and, orientation of component for assembling circumstances. Tolouueirad*et.al*(1997) recognition of relationship between machining parameters and responses are essential for manufacturing industries. Therefore, the main aim of this work is to model and optimize the face milling operation. At present statistical tools, artificial neural network techniques,Francicus et.al.(2006) and Wang (1993), fuzzy logic Suresh Kumar et.al.(2012), Particle swarm optimization Techniques used by Barathiraja et.al.(2012), and non-traditional optimization techniques are used Venkatta rao et.al.(2010) such as for modeling and optimization respectively. Then mechanistic models are not appropriate for newer materials due to experimental risks such as machining condition, hardness, surface roughness etc. So the empirical models are required for every individual machine for its specific performance and its specifications. At the same time, the non-traditional techniques are important for global selection rather than local selection that succeeded by the traditional techniques. So, new trends are required for manufacturing engineering to assess the process uniqueness in machining.Kalpak Jain (1995) , several researchers were used the trial and error experiments and it was tedious, time consuming and more expensive methods. In response, there is an economic need to operate machines as efficiently as possible in order to obtain the required benefits. . Naggendraparashar*et al.* (2003), the achievement of the machining operation depends on the selection of machining process parameters.These parameters play important role such as ensure the quality of product minimize the machining cost and maximize the productivity.

Milling is one of the machining processes, it produces 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 depend on the workpiece and tool materials. Correspondingly two or more cutting edges in milling cutter provide higher material removal rate rather than other machining operations.

Few researchers were concentrated on RSM method for machining problems. RSM is one of the essential statistical tools for calculate the performance characteristics of independent variables. At the same time, lot of researchers were examined the GA and it is one of the best optimization techniques for global optimizationKannan, *et.al*. (2013). Themain aim of this work is to combine the RSM and GA for modeling and to optimize the variables in face milling operation.

2 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 were considered based on machine tool specifications and tool manufacturer recommendations

The metal cutting experiments were conducted on MCV - 400/400S CNC milling machine , tungsten carbide face milling cutter is used for machining the workpiece as shown in figure 1.. The specification of the tool is CAS 12070-12-1. The reasonable range for cutting parameters is taken from machine tool specifications. The machining time is observed by the digital stop watch excluding the tool movement between home position and the work piece.

The input machining parameters considered for this work are speed, feed and depth of cut. The Table 1shows the range and levels of machining parameters used to conduct the experimental work

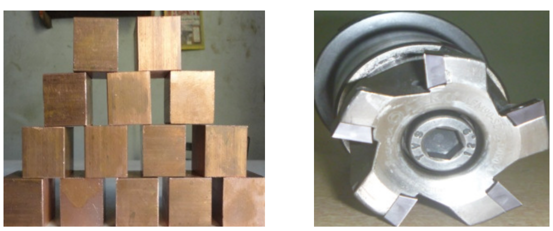


Figure 1 Work pieces and Cutter

Table 1 Range and levels of input parameters

Independent variables	**Unit**	**Ranges**		
		Level I	**Level II**	**Level III**
Spindle speed	rpm	500	710	1000
Feed rate	mm /min	250	435	620
Depth of cut	Mm	0.5	1	1.5

2.1 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 is used to measure the surface roughness of the machined work piece. The surface roughness tester specifications are shown in Table 2.

Table 2 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 preferredsurface roughness value and it depends on the input parameters. It can be help to the process planner for conducting experiments without trial and error method. This can reduce the cost of the experiments.

2.2 Material removal rate (MRR)

The rate at which material is removed from the blank by milling process is known as material removal rate. It is calculated by using the equation (1) and the same is obtainable in Table 3.

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

Where, Q = Material removal rate (mm3/min)
W = Width of cut (mm)
F = Table feed (mm/min)
D = Depth of cut (mm)

2.3 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 3.

2.4 Responsesurface methodology (RSM)

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

The Table 4 shows the MRR ANOVA table. The Model F - Value of 15013.94 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 3 Experimental data

S. No.	Speed	Feed	Depth of Cut	Average MRR	Average Roughness
	rpm	*mm/min*	*mm*	*mm^3/min*	*Seconds*
1	1000	600	0.5	9565.5	1.276
2	1000	550	1	17539.5	2.228
3	1000	500	1.5	23906.25	2.477
4	1000	620	0.5	9871.95	2.167
5	1000	570	1	18066.15	1.7005
6	1000	520	1.5	24710.4	1.9835
7	1000	610	0.5	9662.4	2.375
8	1000	560	1	17743.6	2.867
9	1000	510	1.5	24219.9	1.2335
10	710	426	0.5	6738.255	1.5135
11	710	390.5	1	12351.515	0.7675
12	710	355	1.5	16837.65	1.668
13	710	446	0.5	7146.035	0.7985
14	710	410.5	1	13144.21	1.125
15	710	375	1.5	17991.5625	0.95
16	710	436	0.5	6969.46	1.289
17	710	400.5	1	12531.645	1.1395
18	710	365	1.5	17147.7	1.033
19	500	300	0.5	4683	1.363
20	500	275	1	8580	1.059
21	500	250	1.5	11801.25	0.8845
22	500	320	0.5	5032	0.7155
23	500	295	1	9280.7	1.7565
24	500	270	1.5	12739.275	1.408
25	500	310	0.5	4959.225	2.3995
26	500	285	1	9110.025	1.176
27	500	260	1.5	12462.45	1.406

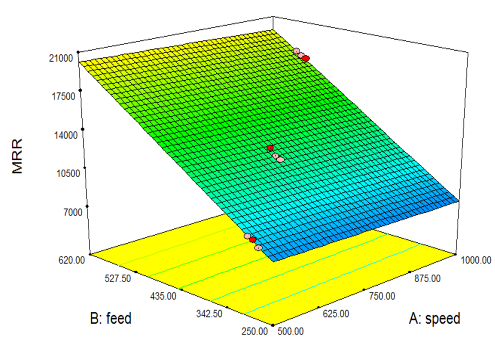
Table 4 ANOVA Table for material removal rate

Source	Sum of Squares	DOF	Mean Square	F Value	p-value prob> F
Model	8.97E+08	6	1.49E+08	15013.94	< 0.0001
A speed	3087.064	1	3087.064	0.310096	0.5838
B Feed	1985723	1	1985723	199.4664	< 0.0001
C depth of cut	56311014	1	56311014	5656.456	< 0.0001
AB	537.5164	1	537.5164	0.053994	0.8186
AC	2005.424	1	2005.424	0.201445	0.6584
BC	2400825	1	2400825	241.1635	< 0.0001
Residual	199103.5	20	9955.175		
Co relaion Total	8.97E+08	26			

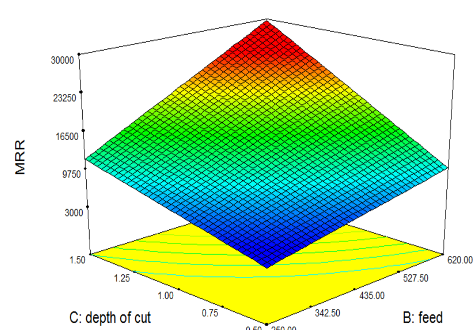
Table 5 ANOVA Table for surface roughness

Source	Sum of Squares	Dof	Mean Square	F Value	p-value Prob> F
Model	60.83899	10	6.083899	10.61233	< 0.0001
A-speed	1.73859	1	1.73859	3.032676	0.0997
B-feed	1.596073	1	1.596073	2.784079	0.1135
C-depth of cut	1.338231	1	1.338231	2.334317	0.1449
AB	0.089205	1	0.089205	0.155603	0.6981
AC	0.045463	1	0.045463	0.079302	0.7816
BC	0.066652	1	0.066652	0.116263	0.7373
A^2	0.056156	1	0.056156	0.097955	0.7581
B^2	0.09901	1	0.09901	0.172706	0.6829
C^2	0.001519	1	0.001519	0.002649	0.9595
ABC	0.047535	1	0.047535	0.082916	0.7769
Residual	9.74586	17	0.573286		
Co Relation Total	70.58485	27			

The Table 5 shows the surface roughness ANOVA table. The “Model F- Value” of 10.61233 implies that the model is significant relative to the noise. The experiments are conducted with 95% 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 is the significant model. The values are greater than 0.1000 and it indicates that the model terms are not significant



(a)



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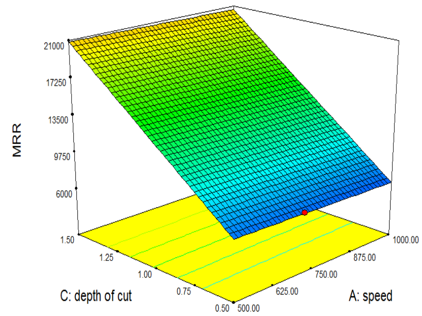
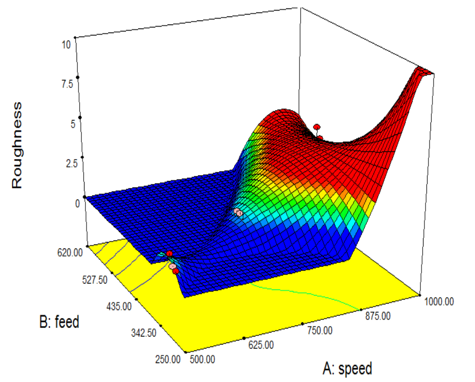
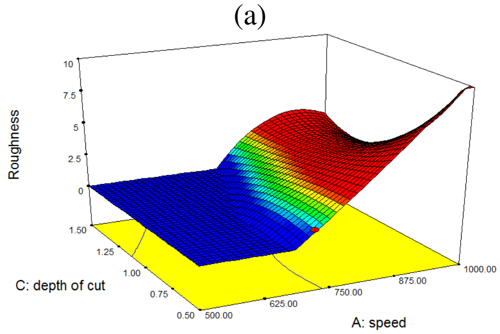


(c)

Figure2 Material removal rate
(a) Speed vsfeed (b) Feed vs depth of cut
(c) Speed vs depth of cut



(a)



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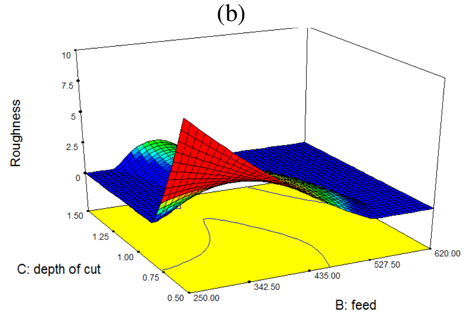

Figure 3 Surface roughness
(a) Speed vs feed (b) Speed vs depth of cut
(c) Feed vs depth of cut

It is observed that there is an increase in feed and depth of cut interaction increases the MRR as shown in Figure 2. There is no significant contribution of interaction in speed & feed and speed & depth of cut on MRR.

From Figure 3, 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.

2.5 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 0.86 R squared value. Hence, these two models are used to optimize the machining parameters in face milling operation.

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.

$$MRR= -171.0787-1.11661 \times V+2.3909\times F -20.61668\times D-2.8142\times 10^{-4}\times V\times F +0.51662\times V\times D+31.035\times F\times D \quad (2)$$

$$SR= -7.37380\times 10^{-4}\times V+4.1683\times 10^{-3}\times F +3.71057\times D-1.5578\times 10^{-4}\times V\times F -0.01306\times V\times D+5.57199\times 10^{-3}\times F\ 5.2994\times 10^{-5}\times V^2+1.13216\times 10^{-4}\times F^2 +9.00604\times 10^{-3}\times D^2+9.670\times 10^{-6}\times V\times F\times D$$

(3)

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

Table 6 Performance evaluations at developed model with experimental values

S. No.	MRR (mm^3/min)			Surface Roughness (μm)		
	Experimental value	Predicted value	% of deviation	Experimental value	Predicted value	% of deviation
1	9565.5	9536.55937	0.303	1.276	1.98322	-55.425
2	17539.5	17437.8352	0.58	2.228	2.15886	3.103
3	23906.25	23787.3609	0.497	2.477	2.14247	13.505
4	9871.95	9889.1008	-0.174	2.167	1.88014	13.238
5	18066.15	18100.7266	-0.191	1.7005	1.9819	-16.548
6	24710.4	24760.6024	-0.203	1.9835	1.89161	4.633
7	9662.4	9712.83008	-0.522	2.375	1.92036	19.143
8	17743.6	17769.2809	-0.145	2.867	2.05906	28.181
9	24219.9	24273.9816	-0.223	1.2335	2.00572	-62.604
10	6738.255	6753.12151	-0.221	1.5135	1.37525	9.134
11	12351.515	12357.1407	-0.046	0.7675	1.27797	-66.511
12	16837.65	16859.4173	-0.129	1.668	1.02875	38.324
13	7146.035	7107.2952	0.542	0.7985	1.35988	-70.304
14	13144.21	13021.6644	0.932	1.125	1.22629	-9.004
15	17991.5625	17834.291	0.874	0.95	0.94076	0.973
16	6969.46	6930.20836	0.563	1.289	1.35624	-5.216
17	12531.645	12689.4025	-1.259	1.1395	1.24081	-8.891
18	17147.7	17346.8541	-1.161	1.033	0.97343	5.767
19	4683	4719.79898	-0.786	1.363	1.22645	10.018
20	8580	8661.76493	-0.953	1.059	1.32011	-24.656
21	11801.25	11827.8558	-0.225	0.8845	1.29948	-46.917
22	5032	5075.15464	-0.858	0.7155	1.27458	-78.138
23	9280.7	9327.4706	-0.504	1.7565	1.35915	22.622
24	12739.275	12803.9115	-0.507	1.408	1.32944	5.58
25	4959.225	4897.47681	1.245	2.3995	1.2392	48.356
26	9110.025	8994.61776	1.267	1.176	1.32831	-12.952
27	12462.45	12315.8837	1.176	1.406	1.30314	7.316
Overall Percentageof deviation			**-0.005**			**-8.418**

3 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 and candidate solutions are randomly generated. New solutions are generated by reproduction, cross over and mutation.

3.1 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 that it requiresformulating the new objective function which consists of MRR and Surface roughness. The Combined Objective function (COF) is creating based on the empirical equations ofsurface roughness and MRR. The COF is given below in equation (4)& (5)

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

$$Min\ COF = 0.5\ (eq.3) - 0.5\ (eq.2) \quad (5)$$

3.2Computational 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. At last, the GA output is shown in Figure 8 for combined objective function of MRR and surface roughness. The most favorable value is obtained at 302th iteration. The subsequent best parameter values are shown in Table 7.

Table 7 Best result from genetic algorithm

Iteration (no.)	Speed (rpm)	Feed (mm/min)	DOC (mm)	Min COF	MRR (mm^3/min)	SR (µm)
302	**765.00488**	419.6388	1.5	-19983.903	19984.8612	0.95869

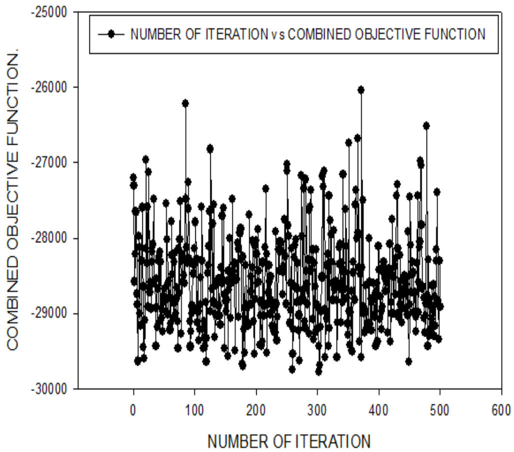

Figure 4. Results of genetic algorithm

4 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 ansuccessful methodology for optimization of machining parameters in face milling operation.
- The performance test of developed models has less percentage of difference with experimental results. The overall accuracy rate of present approach for MRR and surface roughness are 99% and 86% respectively.
- So the developed empirical models with RSM for MRR and surface roughness of copper face milling using tungsten carbide can be used to attain optimal machining parameters.
- For better surface finish, the maximum level of cutting speed with minimum level of feed and depth of cut is suggested.
- The surface roughness and Material removal rate models are combined for attaining combined objective function. It is effective for obtain the best results of incompatible 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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