V V K Lakshmi, Dr K Venkata Subbaiah / International Journal of Engineering Research and Applications (IJERA) ISSN: 2248-9622 www.ijera.com
Vol. 2, Issue 2,Mar-Apr 2012, pp.674-679

Modelling and Optimization of Process Parameters during End Milling of Hardened Steel

V V K Lakshmi[1], Dr K Venkata Subbaiah[2]
[1] Department of Mechanical Engineering VIET, Visakhapatnam
[2]Department of Mechanical Engineering Andhra University Visakhapatnam

In CNC machining, machining parameters are usually selected prior to machining according to hand books. To assure high quality and productivity we need to optimize the machining parameters. In this study, the average surface roughness values obtained when milling EN24 grade steel with a hardness of 260 BHN using solid coated carbide tools were modelled and optimized using response surface methodology. Input variables consist of cutting speed (V), feed rate (f) and depth of cut (d).The output variables are surface roughness and Material removal rates. Variance analysis is conducted using Design Expert 8.0. The response surface methodology (RSM) has been utilized for the postulation of a second order quadratic model in terms of cutting speed, depth of cut and feed. Sufficient numbers of experiments were run based on the 3 level factorial design concept of RSM in order to generate roughness data. The ANOVA technique has been used to verify the adequacy of the model at 95% confidence interval. From the model it was found that feed and speed plays the most dominating role on surface finish. The roughness tends to decrease with decreasing feed and increasing cutting speed.

1. INTRODUCTION

Quality plays a significant role in global market in present day scenario as it directly influences the consumer's satisfaction, moreover surface finish influences mechanical properties such as fatigue, wear,corrosion, lubrication and electrical conductivity. An indication of quality on milling surface is the surface roughness parameter. Advance manufacturing technology offers effective means to achieve good quality. Quality and productivity are two important but conflicting criteria in any machining operations. Surface roughness is not only a quality indicator but also the final stage in controlling the machining performance and the operation cost [1,2].
Surface finish resulting from turning operation has received much attention by researchers whereas process involving multipoint cutters requires attention as the process is complex. In modern industry, one of the trends is to manufacture low cost, high quality products in short time. Automated and flexible manufacturing system s are employed for that purpose ,CNC machines are considered most suitable in FMS .End milling is one of the most widely used metal removal operations in industry because of its ability to remove material faster giving reasonably good surface finish[2]. It is used in a variety of manufacturing industries including aerospace and automotive sectors where quality is an important factor in the production of moulds. Hard milling is a process, work pieces with hardness ranging from 50 to 70 HRC are machined by cutting tools of high hardness and wear resistance at low depth of cut [3].

Surface roughness is a result of many factors including cutting parameters,tool geometry, work piece material ,chatter and cutting fluids. Several researchers have been performed to present the effect of these factors on the surface roughness in end milling of steels and aluminium.Huang and Chen [5] studied an empirical approach to investigate surface roughness in controllable and uncontrollable factors in end milling operation. The effect of cutting tool geometry on milling of AISI 1045 steel for surface roughness model is studied[7] Several studies were carried out to predict surface roughness dependent upon ANN model by means of cutting parameters in end milling and turning operations.The surface roughness has been demonstrated by Huang[6] based on ANN model for end milling of Aluminium 6061 material.The ANN model study has been implemented by Nalbant [7] to create the prediction of surface roughness of steel parts at CNC turning with PVD and CVD coated carbide tools oktem[8] has developed an integrated study of surface roughness to model and optimize the cutting parameters when end milling AISI1040 steel material.[8] has attempted to optimize the conflicting objectives of maximizing the metal removal rate and minimizing the surface roughness using PCA based taguchi method. The influence of tool geometry on quality of surface produced was studied and modelled using response surface methodology [10] Fuzzy and rough sets theory was applied to the machining parameters to optimize the machining cost has been studied [11]HSM of hardened AISI D3 cold work tool steel with CBN cutting tool is studied had concluded with work piece hardness plays a vital role on the performance of tools. CBN tool life and surface finish of work piece proved better for harder material [12]

A method for the estimation of surface roughness ,starting from measured cutting forces in face milling [13]An in process surface roughness adaptive control system in end milling was developed employing a multiple regression model.This study suggested that multiple linear regressions were straight forward and effective for in process adaptive control.

Samanta et al (2008)[14] modelled surface roughness in end milling using soft computing techniques. The ANN and ANFIS techniques were used to demonstrate the case of end milling 6061 aluminium alloy. Machining Hardened steels for moulds and dies with surface roughness constraints are commonly applied in industry and require costly and time consuming traditional operations such as electro discharge machining or grinding Recently research studies has shown that the use of high performance machining operations can be used instead for these operations with important benefits of reducing the lead times and costs(Siller et al) However tool wear process impacts directly surface roughness so optimal cutting parameters are difficult to obtain since they vary according to cutting tool state. Therefore in order to use high performance machining process extra effort has to be conducted in tuning the cutting parameters for optimal machining.

The optimization techniques used in this study are Response surface methodology and Artificial Neural Networks based on Back propagation learning algorithm and tested to control the performance of the trained ANN model. The neural network models have been created based on back propagation learning algorithm when machining operations on the material under wet –dry conditions for surface roughness prediction by the help of input output parameters [15-17]

2 Experimental Set Up and Plan

2.1 Design of Experiments

The design of experimentation has a significant role on the number of experiments needed. Therefore cutting experiments have to be designed In this study a 3 level full factorial were performed to obtain the surface roughness values A total of 27 experiments are conducted at 3 levels for the three input variables speed, feed, depth of cut. Table 1 shows the measured Ra and MRR values.

2.2 Equipment and material

In this research the cutting experiments are conducted on a Vertical CNC Mill Vertical Machining center BMV 45 T20 with a spindle RPM of 10000.

Work piece material

The work piece material used for present work was En24 alloy steel. The chemical composition of En24 is given in Table-1. The hardness of the material is around 250 BHN

Table-1. Chemical composition (wt %) of En24

C (%)	Ni (%)	Mn (%)	Cr (%)	Mo	Si
0.4	1.4	0.5	1.18	0.27	0.28

En 24 steel alloy of 70*70*30 was prepared and utilized for experimentation. Initially the pieces were prepared for experimentation. En24 is nickel molybdenum chromium steel with high strength and toughness. Steel is widely used in the die and mould making industry due to it physical properties and hardness. It is difficult to machine these materials as hardness is > 40 HRC

Tool

Commercially available CVD coated carbide tools have been used. The tools used are flat end mill cutters produced by WIDIA (EM-TiAlN). The tools are coated with TiAlN coating.

Cutter diameter = 8 mm
Fluted length = 38 mm
Helix angle = 300
Hardness = 1570 HV
Density = 14.5 g/cc
Transverse rupture strength =3800 N/mm2
The cutting tool used is solid coated 8 mm Diameter four fluted end mill.

Fig 1 Four flute solid carbide end mill cutter

2.3 Measurement of Surface Roughness

The most practical way of determining the surface roughness is to measure the surface roughness which is defined as the irregularities remained on the surface after machining process. The average roughness Ra is used in present study. Ra is measured using a surface roughness testing instrument which has a probe at one end. During measuring 3mm was set as the cut of length

3 Design of Experiments

3.1 Machining parameters and Levels

The input parameters considered are cutting speed, feed, depth of cut are taken at 3 levels and full factorial design has been applied. There are 27 runs for the design and all the measured output and input parameters are shown in Table 2 below.

Table 2

Level	Cutting Speed (m/min)	Feed Rate (mm/Rev)	Depth of cut (mm)
1	100	0.20	0.2
2	150	0.25	0.3
3	200	0.30	0.4

Table 3 shows the actual Design data and the measured surface roughness and MRR

Std	Run	Speed (RPM)	Feed	DOC (mm)	Ra	MRR
25	1	2000	800	0.2	0.87	1280
1	2	2000	500	0.2	2.12	800
15	3	2000	500	0.35	2.39	1400
16	4	2000	500	0.5	2.56	2000

2	5	2000	200	0.2	0.8	320
23	6	2000	200	0.35	0.88	560
4	7	2000	200	0.5	1.15	800
11	8	4000	800	0.2	0.67	1280
8	9	4000	800	0.35	1.02	2240
20	10	4000	800	0.5	1.06	3200
3	11	4000	500	0.2	0.84	800
12	12	4000	500	0.35	0.9	1400
10	13	4000	500	0.5	0.82	2000
19	14	4000	200	0.2	0.68	320
13	15	4000	200	0.35	0.71	560
21	16	4000	200	0.5	0.66	800
18	17	8000	800	0.2	0.68	1280
17	18	8000	800	0.35	0.73	2240
9	19	8000	800	0.5	1.09	3200
24	20	8000	500	0.2	1.23	800
6	21	8000	500	0.35	1	1400
22	22	8000	500	0.5	1.17	2000
5	23	8000	200	0.2	1.41	320
14	24	8000	200	0.35	1.24	560
7	25	8000	200	0.5	1.6	800

3.2 Statistical analysis

A response surface model was designed and analysed using design expert software Table 2 shows the Analysis of Variance ANOVA was carried out to determine the effect of cutting parameters on the surface roughness. Table 3 and table 4 shows the statistical significance of the cutting parameters and surface roughness A three level factorial response surface methodology with quadratic design model is used.

From Table 3 then Model F-value of 5.53 implies the model is significant. There is only a 0.19% chance that a

Table 4 ANOVA for Response Surface Quadratic Model

Source	Sum of Squares	Mean Square	F-Value	p-value	Prob > F
Model	9	0.31	5.53	0.0019	Significant
A-speed	2.81	1	0.18	3.15	0.0961
B-feed	0.11	1	0.11	1.9	0.1882
C-doc	0.013	1	0.013	0.23	0.6404
AB	0.75	1	0.75	13.25	0.0024
AC	0.067	1	0.067	1.19	0.2918
BC	0.18	1	0.18	3.21	0.0933
A2	1.39	1	1.39	24.63	0.0002
B2	0.37	1	0.37	6.52	0.022
Residual	0.85	15	0.057		
Cor Total	3.66	24			

"Model F-Value" this large could occur due to noise. Values of "Prob > F" less than 0.0500 indicate model terms are significant. In this case AB, A^2, B^2 are significant model terms. Values greater than 0.1000 indicate the model terms are notsignificant.

Table 5

Std. Dev.	0.24	R-Squared	0.7684
Mean	0.042	Adj R-Squared	0.8294
C.V. %	567.95	Pred R-Squared	0. 8416
PRESS	2.78	Adeq Precision	8.674

The "Pred R-Squared" of 0.8416 is close to the "Adj R-Squared" "Adeq Precision" measures the signal to noise ratio. A ratio greater than 4 is desirable. Ratio of 8.674 indicates an adequate signal. This model can be used to navigate the designspace

Final Equation in Terms of Coded Factors:

$$Ln(Ra) = -0.059 + 0.26*A + 0.17 * B + 0.27 * C - 0.44 * A * B - 0.28 * A * C + 0.42 * B * C + 1.06 * A^2 - 0.35 B^2 + 0.047*C^2 \quad (1)$$

Final Equation in Terms of Actual Factors:

$$Ln(Ra) = 0.16097 - 5.00230*10^{-004}*speed + 3.47339*10^{-003}*feed + 0.099925*doc - 3.1424610^{-007} * speed * feed - 1.74474*10^{-004}*speed*doc + 2.96837*10^{-003} * feed * doc + 6.61710*10^{-008}* speed^2 - 2.88307*10^{-006}*feed^2 + 0.29504 * doc^2 \text{ ---------------}(2)$$

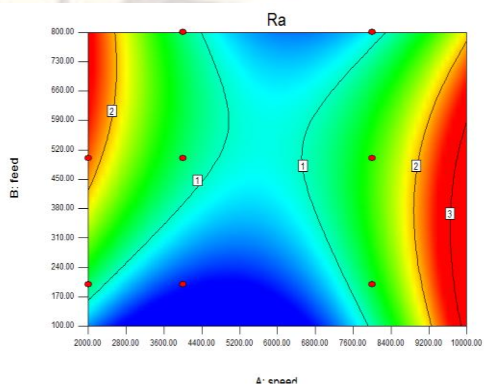

figure 2 Contour plot for response 1 Surface Roughness

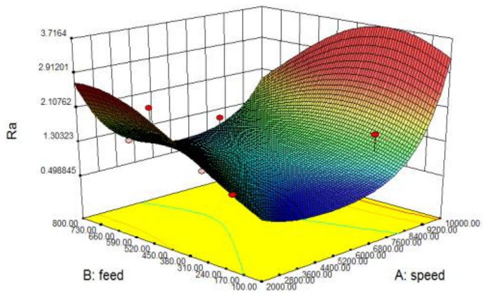

Figure 3 Response surface for surface roughness with significant parameters Speed and feed

Final Equation in Terms of Coded Factors:

MRR=1800.00+0.000 * A+1400.00* B+1440.00 * C+0.000 *A*B+0.000*A* C+1120.0*B*C -(3)

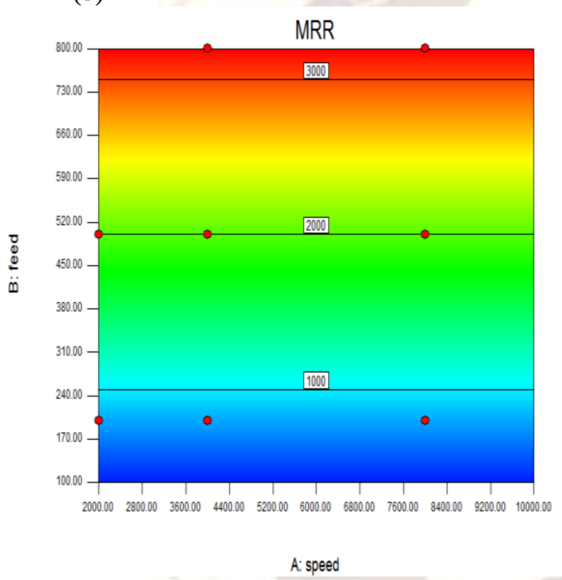

Figure 4 Contour plot for MRR

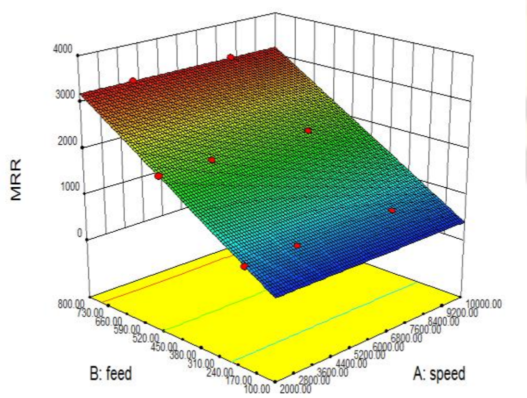

Figure 4 Response surface for Material Removal Rate(MRR)

ANOVA for Response Surface 2FI Model

Response 2 Material removal rate(MRR)

The Model F-value of 63660000.00 implies 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 indicate model terms are significant.In this case A, B, C, AB, AC, BC are significant model terms

Std. Dev.	0.000		
Mean	1294.40	Adj R-Squared	1.0000
C.V. %	0.000		
PRESS	0.000		

The "Pred R-Squared" of 1.0000 is in reasonable agreement with the "Adj R-Squared" of1.0000.

4 Multi Objective Function

The optimization problem for the study is a multi objective optimization problem. The objectives considered are Material removal rate (MRR) and surface roughness.MRR is the measurement of productivity and Surface roughness is the measurement of Quality.MRR can be expressed as product of depth of cut(d) and feed(f) and width of the cutter(w).Equation 4 represents MRR Surface roughness is measured during experimentation and is usually denoted as given by equation 5 where x1,x2,x3 are empirical coefficients.

$$MRR = d*f*w \quad (4)$$

$$Ra = k\,V^{x1} f^{x2} d^{x3} \quad (5)$$

These objectives are conflicting ie to achieve high productivity quality need to be compromised vice versa. The multi objective function is defined is defined using a desirability function approach.[16] Table 4 shows the upper and lower constraints with the weights and desirability factor(importance)

Table 4 Optimization Constraints

Name	Goal	Lower Limit	Upper Limit	Weight	Imp
A:speed	is in range	2000	10000	1	3
B:feed	is in range	100	800	1	3
C:doc	is in range	0.1	0.9	1	3
Ra	minimize	0.66	1.56	1	3
MRR	maximize	320	3200	1	

Once the objective function defined and the constraints imposed the results obtained by design expert are as shown in table 5 with a desiribilty factor of .933 which is high.So the optimum value of speed is 6300 RPM ,feed 800 mm/min depth of cut is 0.5 for a minimum surface roughness value of .47

Table 5

OptimumValues

Num	speed	feed	doc	Ra	MRR	Desiribility
1	6338.96	800.00	0.50	0.67643	93200	0.933

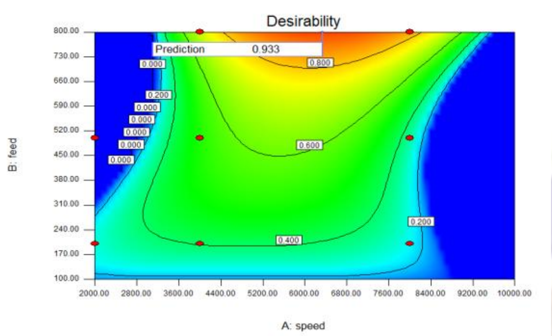

Figure 5 contour plot for speed vs feed for given desirability

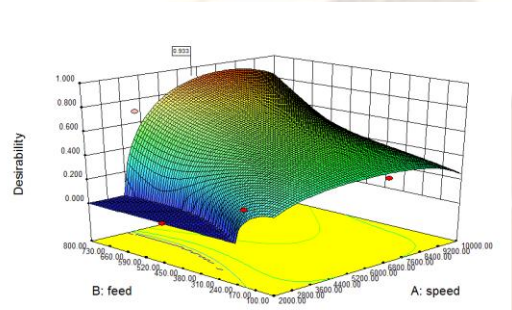

Figure 6 Response surface for optimized output

5 Optimization Results

The optimum cutting parameters were obtained maximizing the overall desirability function which depends on the models and the individual desirability and weights coefficients the results of the optimum procedure showed the optimum conditions as Speed 160m/min and feed 800mm/min and depth of cut 0.5 mm

Table 6 Optimization Results From RSM for Surface Roughness and MRR optimization

Two-sided		Confidence = 95%			n =1
Factor	Name	Level	Low Level	High Level	Std. Dev.
A	Speed	6339	2000	8000	0
B	Feed	800	200	800	0
C	Doc	0.5	0.2	0.5	0
Response	Prediction	Std Dev	SE (n=1)	95% PI low	95% PI high
Ra	0.77	0.23		0.424	1.42
MRR	4000	0	0	3200	3200

The roughness values obtained from different trials are presented in last column of Table I. A second order quadratic model has been intended to develop which will take into account the quadratic and interactive effects beside the individual factors. Table III presents each of the estimated effects, along with their interactions and standard error. The ANOVA table tests the statistical significance of each effect by comparing the mean square against an estimate of the experimental error . In thiscase, Values of "Prob > F" less than 0.0500 indicate model terms are significant. In this case AB, A^2, B^2 are significant model terms at confidence interval of 95%. Values greater than 0.1000 indicate the model terms are not significant. Cutting speed, axial depth of cut and feed are Expressed in logarithmic transformation. Since all the three parameters are under the same logarithmic scale, the factor with highest value of coefficient possesses the most dominating effect over the response.
From the model, feed has the most significant effect over roughness, followed by the cutting speed. However, axial depth of cut tends to have very little effect on surface finish. Fig. 1 shows the contours of experimental results and predicted surface roughness values generated by the Quadratic response model. From Fig. 1 it can be affirmed that the 2nd order model is adequate to predict the surface roughness values closer to the experimental results The response surface plot is a good tool to estimate the region of optimum response, which is basically similar to the 3-D wire frame plot Fig. 2 and 3 show the logarithmic roughness as the function of and, for the minimum and maximum values of B. As it is observed from Fig. 2 and 3, roughness increases with increasing feed and decreasing cutting speed. Equation is valid for end milling of En 24 alloy steel using Solid coated carbide tool cutting speed *V*, feed *f,* and axial depth of cut, A : 161.70m/min $\leq$ V $\leq$ 232.10 m/min, 1.17 mm $\leq$doc $\leq$ 2.55 mm, and 200 mm/min $\leq$ feed $\leq$ 800 mm/tooth, respectively.

6. CONCLUSION

This paper presents an experimental investigation on surface finish and material removal rate during the high speed end milling of En24 alloy steel in order to develop an appropriate roughness prediction model and optimize the cutting parameters using RSM. Based on the response surface concept and 3 level factorial, adequate numbers of experiments were performed to generate the roughness data. These results were used to develop a 2nd order quadratic model to predict surface roughness. The general conclusions from the current study can- be summarized as follows:

1. RSM has been proven to be an efficient method to predict the surface finish during end-milling of En 24 alloy steel. It also reduces the total numbers of experiment quite significantly.
2. The quadratic second order models, developed to predict the surface roughness value, could provide predicted values of surface roughness pretty close to

the actual values found in the experiments. The model was checked at 95% confidence level for the adequacy.

3. Feed possesses the most significant effect on roughness followed by cutting speed. However, depth of cut appears to have very little effect over roughness value. An increment of cutting speed and decrement of feed will result in better surface quality in terms of roughness.
4. Interaction effects between cutting speed and depth of cut also possesses a major effect over the surface roughness value.

References

1. Boothroyd G ,Knight WA(1989) Fundamentals of machining and machine tools.Marcel Dekker Inc, New York
2. Dagnal H (1986) Exploring surface texture Rank Taylor Habson corp england
3. Singh D Rao PV(2007)A surface roughness prediction model for hard turning process Int J Adv Manuf Tech.,32:1115-1124
5. Huang BP,Chen JC(2008) Artifical –Neural Network Based surface roughness Pokayoke system for end milling operations Neuro computing 71:544-549 doi 10.1061
6. Nalbant M Gokkaya H The experimental investigation of effects of uncoated and coated cemented carbide inserts and cutting parametsr on surface in CNC turning Rob Comput Integr manuf(in press)
8. H Oktem (2009) An integrated study of surface roughness for modelling and optimization of cutting parameters during end milling opration Int J Adv Manuf Technol(2009)43:852-861
9. Sanjith Moshat Saurav Datta Asish Bandyopahyay et al Optimization of CNC end milling process parameters using PCA based Taguchi method Int J of Engineering Science and Technologtion of y Vol 2 N0 1 2010 pp 92-102
10. N Suresh kumar reddy Selection of optimum tool geometry and cutting conditions using a surface roughness prediction model for end milling : Int J Adv Manuf Technol(2005)43:1202-1210
11. Yajun Lou Zhenliang Li Minghui Application Fuzzy and rough sets theory was applied to the machining parameters to optimize the machining Int J Adv Manuf Technol(2006)28:1071-1077
12. E Aslan N camuscu High Speed End Milling of hardened AISI D3 cold work tool steel with CBN cutting tool G U Journal of science 453:458 (2005)
14. Adaptive Control Optimization of Cutting Parameters for High Quality Machining Operations based on Neural networks and Search Algorithms Advances in robotics, Automation and Control pp472 Itech Vienna
13. Rosales A Prediction of surface roughness by registering the cutting forces in face milling Eur Journal of Science and technology 41(2):228-237
15. Samantha B Prediction of workpiece surface roughness using soft computing Int J Adv Manuf Technol(2006)32:1115-1124
16. J V Abelian Adaptive control optimization of cutting parameters for high quality machining operations based on search algorithms Advances in robotics automation and control ISBN 78-953-7619-16-9 pp 472