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MODELLING OF SURFACE ROUGHNESS IN MACHINING

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Abstract

In this globalize and competitive world of today, the only way to survive for a company is to produce high quality products and services. In the increasing demand of quality and tight tolerances, surface roughness became the most critical quality criteria in machining. The necessity of the processes to be able to work properly in the first time and all the time is an obligation. In this paper, in order to model the quality characteristic in machining, the experiments are done and their results are evaluated. Controllable surface roughness is the key factor in capacity and cost strategies. In order to maintain these goals surface roughness is modeled by design of experiment techniques and the cutting conditions are optimized by the heuristic algorithms for accuracy in cutting and decrease in costs.

Keywords: Quality, Experimental Design, Response Surface Methodology, Surface Roughness.

TALAŞLI İMALATTA YÜZEY PÜRÜZLÜLÜĞÜNÜN MODELLENMESİ

Özet

Günümüz global ve rekabetçi dünyasında firmaların hayatta kalabilmesinin tek yolu kaliteli mal ve hizmet üretmeleridir. Artan kalite talebi ve daralan toleranslar, yüzey pürüzlülüğünü, talaşlı imalatın en kritik kalite kriteri haline getirmiştir. Proseslerin ilk seferde ve her seferinde, hedef değerde doğru çalışması artık bir gerekliliktir. Bu makalede, talaşlı imalatta bir kalite karakteristiği olan yüzey pürüzlülüğünün modellenmesi için deneyler yapılmış ve sonuçları değerlendirilmiştir. Minumum yüzey pürüzlülüğünün elde edilmesi maliyet ve kapasite stratejileri açısından çok önemlidir. Bu hedeflerin gerçekleştirilebilmesi için deney tasarımı yöntemleri ile kesme şartlarının modellenmesi sağlanmış, sezgisel algoritmalarla da optimize edilerek kesme işlemlerinde kesinlik ve maliyetlerde düşüş hedeflenmiştir.

Anahtar Kelimeler **:** Kalite, Deney Tasarımı, Yüzey Yanıt Yöntemi, Yüzey Pürüzlülüğü

INTRODUCTION

Machinability of a material provides an indication of its adaptability to be manufactured by a machining process. In general, machinability can be defined as an optimal combination of factors such as low cutting force, high material removal rate, good surface integrity, accurate and consistent work piece geometrical characteristics, low tool wear rate and a good curl or chip breakdown chips. In machinability studies, Statistical design of experiments is used quite extensively. Statistical design of experiments refers to the process of planning the experiment so that appropriate data can be analyzed by statistical methods, resulting valid and objective conclusions. Design methods such as factorial design response surface methodology (RSM) and Taguchi Methods are now widely use in place of one factor at a time experimental approach which is time consuming and exorbitant in cost. (Nooridin, et al., 2004)

In this paper the effect of the most important factors on the surface roughness is investigated. These factors are speed, feed and depth of cut. The experiments are done in the Clausing Colchester 13-inch flat bed lathe machine The cutting, is done under dry conditions with the Carbid Rhomboid insert, and the cutting material is AISI 4140.The surface roughness are measured by TR100 profilometer. For the statistical analysis of the experiments Minitab 14 soft ware is used. The effects of the three factors on surface roughness are described by using Response Surface Methodology. The experimental plan was based on Box-Behnken design. First order and second order model predicting equations for surface roughness have been established by using the experimental data. This paper presents a study of a development of a surface roughness model for a turning operation. Differential Evolution Algorithm is used to find optimum values of the factors which will give the minimum surface roughness.

LITERATURE REVIEW

Due to the widespread use of highly automated machine tools in the industry, manufacturing requires reliable models and methods for the prediction of output performance of machining processes. The prediction of optimal machining conditions for good surface finish and dimensional accuracy plays a very important role in process planning. The present work deals with the study and development of a surface roughness prediction model for machining mild steel, using Response Surface Methodology (RSM). The experimentation was carried out with TiN-coated tungsten carbide (CNMG) cutting tools, for machining mild steel work-pieces covering a wide range of machining conditions. A second order mathematical model, in terms of machining parameters, was developed for surface roughness prediction using RSM. This model gives the factor effects of the individual process parameters. An attempt has also been made to optimize the surface roughness prediction model using Genetic Algorithms (GA) to optimize the objective function. The GA program gives minimum and maximum values of surface roughness and their respective optimal machining conditions (Suresh et. al., 2002)

Majority of machining operations require the cooling and lubricating action of cutting fluids. But, due to ecological and human health problems, manufacturing industries are now being forced to implement strategies to reduce the amount of cutting fluids used in their production lines. In the present work, experimental studies have been conducted to see the effect of tool geometry (radial rake angle and nose radius) and cutting conditions (cutting speed and feed rate) on the machining performance in dry milling with four fluted solid TiAlN coated carbide end mill cutters. The significance of process parameters on surface finish has been evaluated using analysis of variance. Mathematical models have been developed for surface roughness prediction using Response Surface Methodology. Then the optimization has been carried out with Genetic Algorithms using the surface roughness models developed and validated in this work. This methodology helps to obtain the best possible tool geometry and cutting conditions for dry milling. (Reddy and Rao, 2005)

Surface roughness and tolerances are among the most critical quality measures in many mechanical products. As competition grows closer, customers now have increasingly high demands on quality, making surface roughness become one of the most competitive dimensions in today's manufacturing industry. Surfaces of a mechanical product can be created with a number of manufacturing processes. This research applies the fractional factorial experimentation approach to studying the impact of turning parameters on the roughness of turned surfaces. Analysis of variances is used to examine the impact of turning factors and factor interactions on surface roughness. Finally, contributions are summarized and future research directions are highlighted. (Feng, 2001)

Surface roughness plays an important role in product quality. This paper focuses on developing an empirical model for the prediction of surface roughness in finish turning. The model considers the following working parameters: work piece hardness (material); feed; cutting tool point angle; depth of cut; spindle speed; and cutting time. One of the most important data mining techniques, nonlinear regression analysis with logarithmic data transformation, is applied in developing the empirical model. The values of surface roughness predicted by this model are then verified with extra experiments and compared with those from some of the representative models in the literature. Metal cutting experiments and statistical tests demonstrate that the model developed in this work produces smaller errors than those from some of the existing models and have a satisfactory goodness in both model construction and verification. Finally, further research directions are presented. (Feng and Wang, 2002)

Erzurumlu and Öktem, (2007) In their study, they develop response surface (RS) model and an artificial neural network (ANN), to predict surface roughness values error on mold surfaces. In the development of predictive models, cutting parameters of feed, cutting speed, axial–radial depth of cut, and machining tolerance are considered as model variables. For this purpose, a number of machining experiments based on statistical three-level full factorial design of experiments method are carried out in order to collect surface roughness values. An effective fourth order RS model is developed utilizing experimental measurements in the mold cavity. A feed forward neural network based on back-propagation is a multilayered architecture made up of one or more hidden layers (2 layers–42 neurons) placed between the input (1 layer–5 neurons) and output (1 layer-1 neuron) layers. The response surface model and an artificial neural network are compared with manufacturing problems such as computational cost, cutting forces, tool life, dimensional accuracy, etc.

Optimum selection of cutting conditions importantly contribute to the increase of productivity and the reduction of costs, therefore utmost attention is paid to this problem in this contribution. In this paper, a neural network-based approach to complex optimization of cutting parameters is proposed. It describes the multi-objective technique of optimization of cutting conditions by means of the neural networks taking into consideration the technological, economic and organizational limitations. To reach higher precision of the predicted results, a neural optimization algorithm is developed and presented to ensure simple, fast and efficient optimization of all important turning parameters. The approach is suitable for fast determination of optimum cutting parameters during machining, where there is not enough time for deep analysis. To demonstrate the procedure and performance of the neural network approach, an illustrative example is discussed in detail. (Zuperl and Cus, 2003)

Jusso et al. (2000), Kim at al. (2007) and Chen et al. (1999) used Wavelet Technique For determining surface roughness, also Chang et al. (2005) combined the Response surface methodology and wavelet transform technique.

Zhang et al. (2006) in their paper, they present a study of the Taguchi design application to optimize surface quality in a CNC face milling operation. Maintaining good surface quality usually involves additional manufacturing cost or loss of productivity. The Taguchi design is an efficient and effective experimental method in which a response variable can be optimized, given various control and noise factors, using fewer resources than a factorial design. This study included feed rate, spindle speed and depth of cut as control factors, and the noise factors were the operating chamber temperature and the usage of different tool inserts in the same specification, which introduced tool condition and dimensional variability. An orthogonal array of L9(34) was used; ANOVA analyses were carried out to identify the significant factors affecting surface roughness, and the optimal cutting combination was determined by seeking the best surface roughness (response) and signal-to-noise ratio. Finally, confirmation tests verified that the Taguchi design was successful in optimizing milling parameters for surface roughness.

EXPERIMENTAL DESIGN AND ANALYSIS

In the analysis Box-Behnken Design is used. The design is composed of three factors, and each of them has three levels and three central points are added to the design.

Table 1 Factor levels

Level	Surface Speed	Feed Rate (mm/rev)	Depth of cut (mm)
Low	250	0.1	1.5
Medium	300	0.2	2
High	350	0.3	2.5

Estimated Regression Coefficients for Surface Roughness (First Order Model)

Term	Coef	SE Coef	T	P
Constant	3.394	3.0248	-1.122	0.268
Dept of cut	0.691	0.3466	1.995	0.053
Feed	-0.598	0.1592	3.758	0.001
Speed	0.503	0.5272	0.954	0.346

S = 0.4352 R-Sq = 31.7% R-Sq(adj) = 26.7%

Analysis of Variance for Surface Roughness

Source	DF	Seq SS	Adj SS	Adj MS	F	P
Reg.	3	3.6059	3.6059	1.20198	6.35	0.001
Linear	3	3.6059	3.6059	1.20198	6.35	0.001
R.Error	41	7.7669	7.7669	0.18944		
L.O.Fit	9	7.3832	7.3832	0.82035	68.42	0.000
P. Error	32	0.3837	0.3837	0.01199		
Total	44	11.3728				

$Y=-3.3944+0.6914X_1-0.5983X_2+0.5032X_3$ The first order equation, obtained from modeling of the surface roughness.

$R_a = C\, d^{k1} f^{k2} v^{k3}$ …. ……. C is a constant, $k_{1,2,3}$ are the parameters. They are logarithmically transformed and these linear equations are obtained.

$\ln R_a = \ln C + k_1 \ln d + k_2 \ln f + k_3 \ln v$

k_1: 0.6914-----------$e^{0.6914}$ = 1.997

k_2: -0.5983----------$e^{-0.5983}$ = 0.55

k_3:0.5032------------$e^{0.5032}$ = 1.654
C: -3.3944 -----------$e^{-3.3944}$ = 0.034
$R_a = 0.034\, d^{1.997} f^{0.55} v^{1.654}$

Minitab Software is used for the statistical analysis. One of the main factors cutting speed is insignificant with the value of 0.268. Since it is one of the three main factors it can not be eliminated. Due to the R Sq value being significantly low for the first model (R Sq = 31.7%) a second order model has to be attempted since this R Sq value renders the first model to be invalid.

Although the R-sq value is high in the second order model, in the % 95 confidence level, the feed rate and cutting speed factor interactions are insignificant with the 0.2 value. The interaction of the two factors has been removed and reanalyzed in other words the coefficients have to be deleted through backward elimination. With the removal of the interaction terms of the factors feed rate and cutting speed the obtained model is proper, all the factors and their second degree interactions are significant.

Estimated Regression Coefficients for Surface Roughness (Second Order Model)

Term	Coef	SE Coef	T	P
Constan	552.2	49.9506	11.054	0.000
Depth of cut	49.6	5.5578	8.927	0.000
Feed	1.8	0.5925	3.116	0.004
Speed	-200.2	17.5184	-11.428	0.000
D.o.c.*D.o.c.	6.4	0.6752	9.541	0.000
Feed * Feed	0.8	0.1561	5.190	0.000
Speed * Speed	18.2	1.5392	11.847	0.000
D.o.c.* Feed	0.6	0.2897	2.198	0.034
D.o.c * Speed	-9.9	0.9601	-10.290	0.000

S = 0.1437 R-Sq = 93.5% R-Sq(adj) = 92.0%

Analysis of Variance for Surface Roughness

Source	DF	Seq SS	Adj SS	Adj MS	F	P
Reg.	8	10.6291	10.6291	1.32864	64.32	0.000
Linear	3	3.6059	4.7108	1.57025	76.01	0.000
Square	3	4.7259	4.7327	1.57757	76.37	0.000
Int.	2	2.2973	2.2973	1.14867	55.61	0.000
R.Error	36	0.7437	0.7437	0.02066		
L.O.Fit	4	0.3600	0.3600	0.09000	7.51	0.000
P. Error	32	0.3837	0.3837	0.01199		
Total	44	11.3728				

$$\text{Min } Y = 552.2 + 49.6X_1 + 1.8X_2 - 200.2X_3 + 6.4X_1^2 + 0.8X_2^2 + 18.2X_3^2 + 0.6X_1X_2 - 9.9X_1X_3$$

$0.405465 < X_1 < 0.916291$
$-2.30259 < X_2 < -1.60944$
$5.52146 < X_3 < 5.85793$

Test for significance of the regression model is performed as an ANOVA procedure by calculating the F- ratio, which is the ratio between the regression mean square and the mean square error. This ratio is used to measure the significance of the model under investigation.

Y is the logarithmic transformation of the surface roughness. X_1, X_2, X_3, and the constraints are in the logarithmic transformed form of the depth of cut, feed rate and speed. In the obtained model all the variables are significant and the R-Sq is %93.5. Sequence of run in Box Behnken design is like that

Run	A	B	C
1	–	–	0
2	+	–	0
3	–	+	0
4	+	+	0
5	–	0	–
6	+	0	–
7	–	0	+
8	+	0	+

Run	A	B	C
9	0	–	–
10	0	+	–
11	0	–	+
12	0	+	+
13	0	0	0
14	0	0	0
15	0	0	0

A proper cutting condition is extremely important task because these determine surface quality of manufactured parts. In order to know surface quality and dimensional precision properties in advance, it is necessary to employ theoretical models making it feasible to do predictions in function of operation conditions. The response surface method (RSM) is practical, economical and relatively easy for use. The experimental data were utilized to build mathematical model for the first and second order model by regression method. (Sahin and Motorcu, 2005)

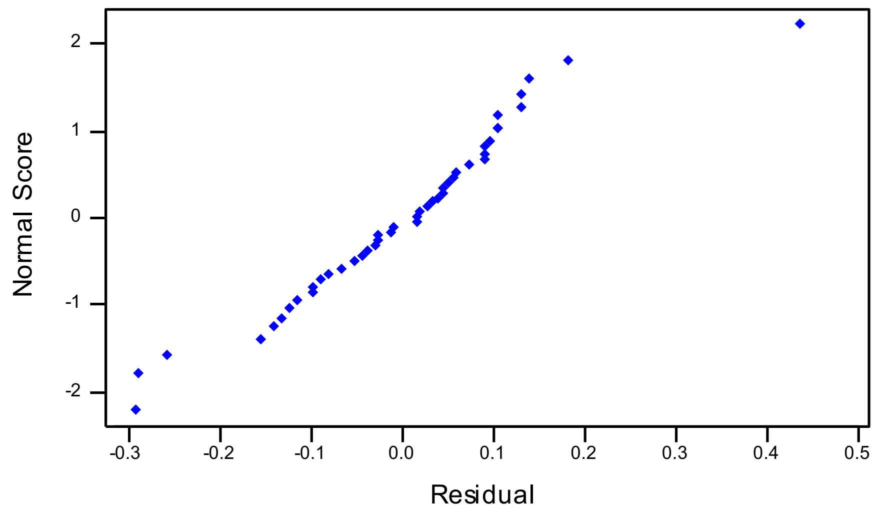

Figure 1 Normality Plot of the Residuals

The residuals which are the difference between the respective, observe responses and the predicted responses are examined using the normal probability plots of the residuals and the plots of the residuals versus the predicted response. The model is adequate because the points on the normal probability plots of the residuals form a straight line, which can be seen in Figure1.

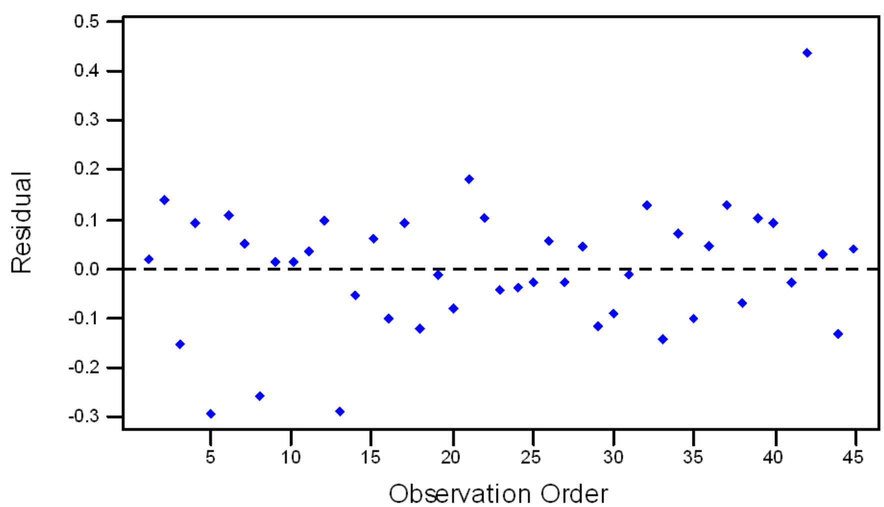

Figure 2 Residuals versus the Order of the Data

The plots of the residuals versus the Order of the Data is structure less and they have no obvious patterns, there is no negative or positive trend so it can be said that there is no correlation the residuals are independent that can be seen in Figure 2.

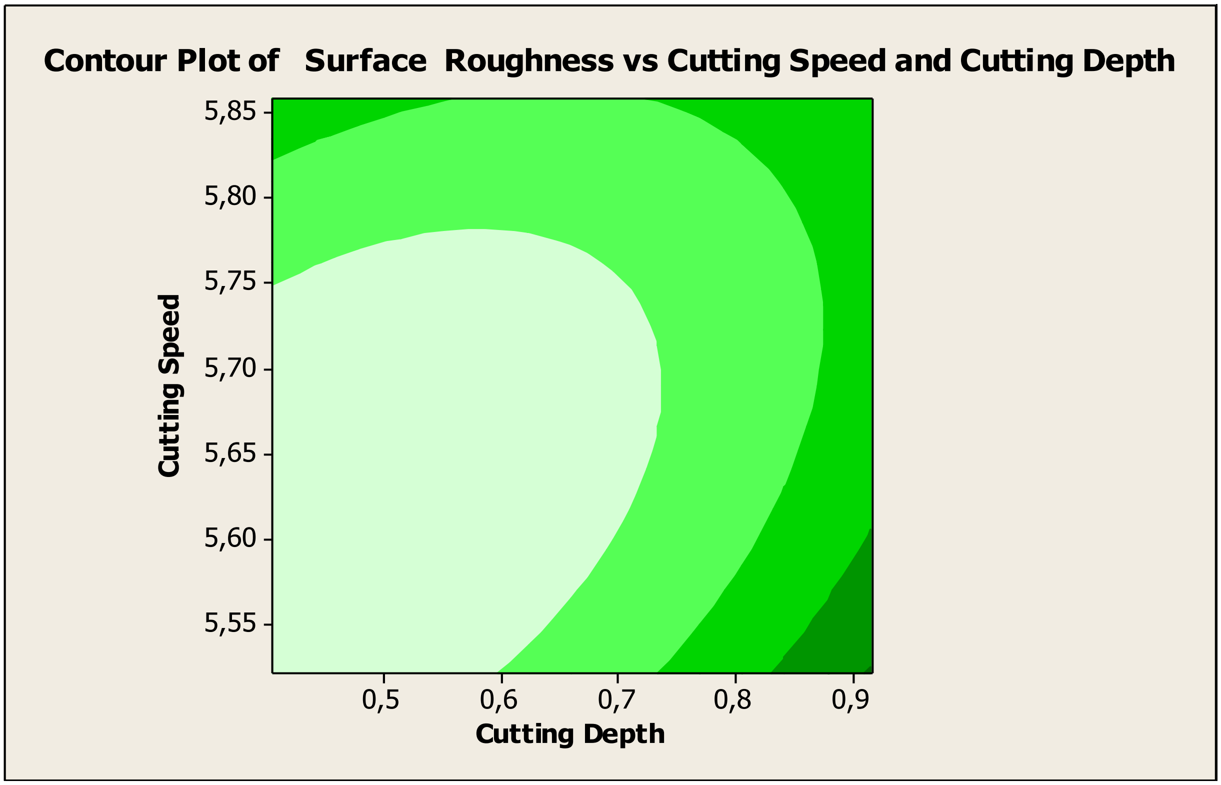

Figure 3 The Surface Roughness Contours in Cutting Speed and depth of cut plane

In the Figure 3 between the cutting speed and depth of cut with their elliptical figure there is strong, negative, second degree relationship can bee seen. Also in figure 4, in the 3D graphics it can bee seen that when the cutting speed is low and the depth of cut is high the surface roughness is in its maximums. Between the feed rate and depth of cut there is a weak relationship with the 0.6 value. The 3D surface graphs for surface roughness which have curvilinear profile in accordance to the quadratic model fitted are obtained and the the adequacy of the model verified. The obtained model will be optimized by one of the heuristics. Differential Evolution.

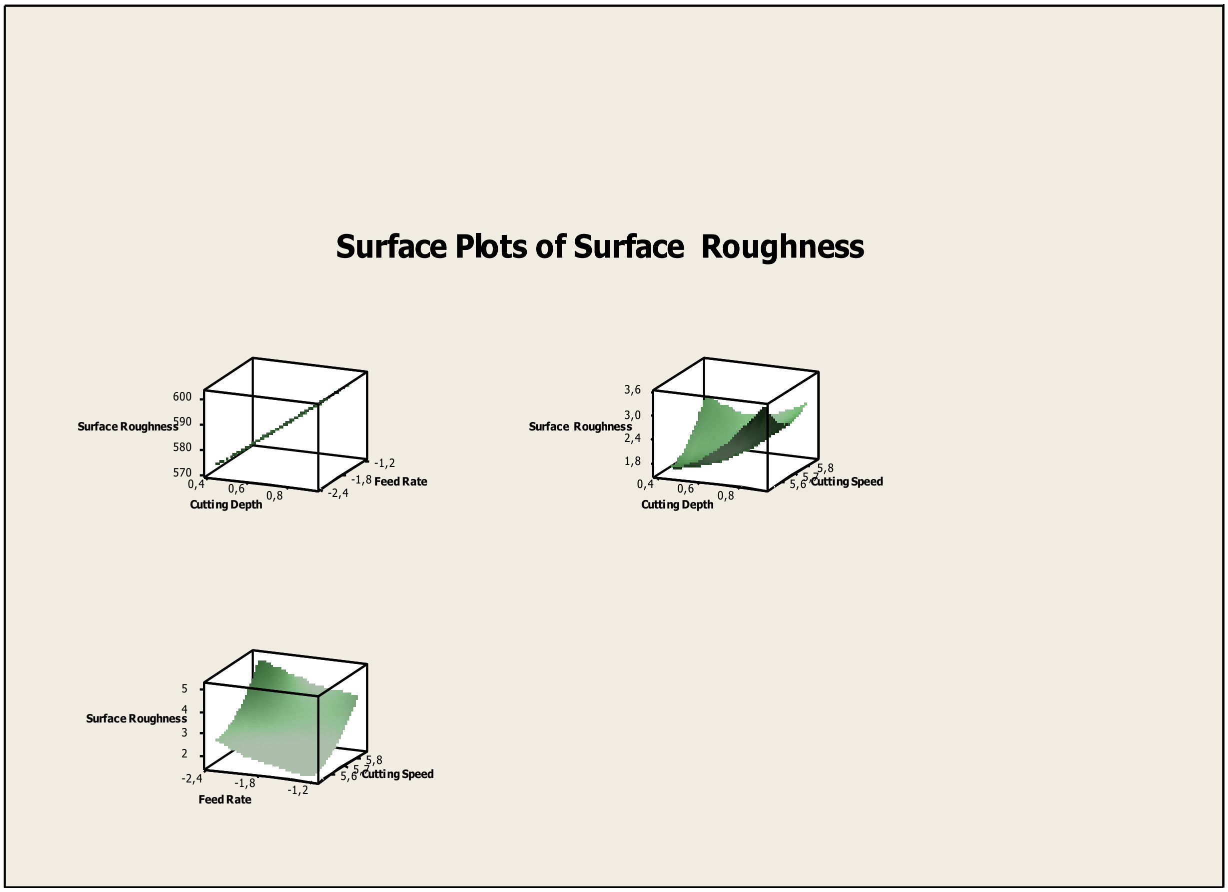

Figure 4 3D surfaces Graph for the impact of the cutting Factors on the Surface Roughness

Optimization with Differential Evolution Algorithm

Differential Evolution (DE) is a simple evolutionary algorithm for numerical optimization whose most novel feature is that it mutates vectors by adding weighted, random vector differential to them. The Differential Evolution is controlled by just three variables: the population size, the mutation Scaling factor, F, and the crossover constant, CR. (Price, 1997, p: 153) It is efficient especially in optimization of continuous variables. It is a heuristic whose operator's works like genetic algorithm. The codes are in written in Matlab 7.0.

Differential evolution whose main design emphasis is real parameter optimization is based on a mutation operator, which adds an amount obtained by the difference of two randomly chosen individuals of the current population, in contrast to most evolutionary algorithms, in which the mutation operator is defined by a probability function. The pseudo –code of the differential evolution algorithm adopted in this work can be seen below. (Bacerra, Coello, 2005)

Do

For each individual j in the population

Generate three random integers, r_1, r_2, $r_3 \in (1, popsize)$

$with\, r_1 \neq r_2 \neq r_3 \neq j$

$Generate\, a\, random\, \mathrm{int}\, eger\, i_{rand} \in (1, n)$

$For\, each\, parameter\, i$

$$x'_{i,j} = \begin{Bmatrix} x'_{i,j} + F*(x_{i,r1} - x_{i,r2} & if\;\; rand_i(0,1) < CR\; or\; i = i_{rand}\, otherwise \\ x_{i,j} & \end{Bmatrix}$$

$End\, For$

$\mathrm{Re}\, lace\, X_j\, with\, the\, child\, x'_{,j}\;\, if\;\, x'_{,j}\;\, isbetter$

$End\;\, for$

$Until\, the\, ter\, \mathrm{min}\, ation\, condition\, is\, achieved$

Differential Evolution Algorithm Parameters:
F = 1
NP: Population size= 10
Gmax: Iteratation number = 1000
CR: Crossover rate= 0.8

Min Y=552.2 + 49.6X1+1.8X2-200.2X3+6.4X12+0.8X22+18.2X32+0.6X1X2-9.9X1X3

Y is the logarithmic transformation of the surface roughness. X_1, X_2, X_3, and the constraints are in the logarithmic transformed form of the depth of cut, feed rate and speed

$0.405465 < X_1 < 0.916291$
$-2.30259 < X_2 < -1.60944$
$5.52146 < X_3 < 5.85793$

The results of the optimization by the Differential Evolution Algorithm:
X_1: 0.5743 -----------$e^{0.5743}$ =1.7759
X_2:-1.6094------------$e^{-1.6094}$=0.2
X_3:5.6560---------------$e^{5.6560}$=286.002
R_{min} = - 0.8479 = $e^{-0.8479}$=0.4283

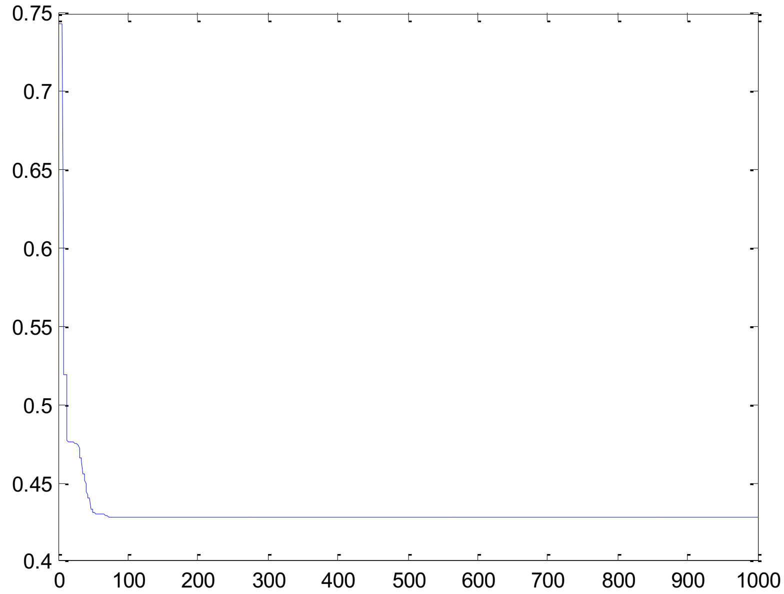

Figure 5 The Value of the Goal Fuction through iterations by the Differantial Evolution

CONCLUSION

Box Behnken have proposed some three-level designs for fitting response surfaces. These designs are formed by combining 2^k factorials with incomplete block designs. The resulting designs are usually very efficient in terms of the number of required runs, and they are either rotatable or nearly rotatable. The box Behnken design does not contain any points at the vertices of the cubic region created by the upper and lower limits for each variable. This is advantageous when the points on the corners of the cube represent factor level combinations that are prohibitively expensive or impossible to test because of physical process constraints. (Montgomery, 2005, p: 431)

In this paper, first order and second order model predicting equations for surface roughness have been developed using response surface methodology for machining mild steel with coated tools. The established equations clearly show that the depth of cut was main influencing factor on the surface roughness. It decreased by increasing cutting speed and increased by increasing the depth of cut. In addition to the analysis of variance for the second order model shows that the interaction terms; depth of cut with speed and depth of cut with feed rate and the square terms are statistically insignificant. The prediction of surface roughness experiments are done with 95% confidence level.

In the result of the optimization by the Differential Evolution the cutting parameters of depth of cut, feed rate and speed are: 1.7759, 0.2, and 286.002. If the machine setting is fixed to these values the surface roughness of 0.4283 will be obtained which is a good value for most of the surface roughness improvement studies. In Figure 5, the optimum value for the surface roughness started to decrease from 0.75 to 0.4283, after 100 iterations and reached to the steady state.

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