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# THE USE OF RESPONSE SURFACE METHODOLOGY FOR PREDICTION AND ANALYSIS OF SURFACE ROUGHNESS OF AISI 4140 STEEL

## UPORABA METODOLOGIJE ODGOVORA POVRŠINE ZA NAPOVED IN ANALIZO HRAPAVOSTI PRI JEKLU AISI 4140

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This paper utilizes regression modeling in turning process of AISI 4140 steel using Response Surface Methodology (RSM) with rotatable Central Composite Design (CCD). A quadratic model was developed for the prediction and analysis of the relationship between the cutting conditions and surface roughness. In the development of predictive models, cutting parameters of cutting speed, feed rate and depth of cut were considered as model variables, surface roughness were considered as a response variable. The statistical analysis showed that, cutting speed and feed rate have the most significant effect on surface roughness. The predicted values was found similar to the actual values. The alternative solutions of the optimization approach using desirability functions were used to determine the optimum processing conditions.

Keywords: turning, surface roughness, optimization, RSM (CCD)

V tem delu uporabljamo regresijsko modeliranje struženja jekla AISI 4140 po metologiji odgovora površine (RSM) z vrtljivim središčnim kompositnim načrtom (CCD). Kvadratičen model je bil razvit za napovedovanje in analizo odvisnosti med pogoji struženja in hrapavostjo površine. Pri razvoju napovedovalnih modelov so bili parametri struženja hitrost, podajanje in globina upoštevani kot spremenljivke modela, hrapavost površine pa kot spremenljivka odgovora. Statistična analiza je pokazala, da imata hitrost struženja in globina podajanja največji vpliv na hrapavost površine. Napovedane vrednosti so bile podobne izmerjenim. Za optimizacijo pogojev procesa so bile uporabljene alternativne želelne funkcije.

Ključne besede: struženje, hrapavost površine, optimizacija, RSM (CCD)

## 1 INTRODUCTION

The surface quality is an important parameter to evaluate the productivity of machine tools as well as machined components. Hence, achieving the desired surface quality is of great importance for the functional behaviour of the mechanical parts. Surface quality is generally associated with surface roughness. The surface roughness of machined parts is known to have considerable effect on some properties such as wear resistance and fatigue strength [1-3].

Several researchers have developed mathematical models to predict the surface roughness in terms of various process parameters during turning of different materials. Sahin and Motorcu [1] machined the hardened AISI 1040 steel with triangular and square tools in different machining conditions and modeled the surface roughness by using RSM. Sahin and Motorcu [2] developed the surface roughness model in terms of main cutting parameters such as cutting speed, feed rate and depth of cut using RSM. Kopac and Bahor [3] examined the changes in surface roughness of AISI 1060 and AISI 4140 steels and analyzed the effect of cutting parameters by using RSM. Noordin et al. [4] developed the empirical models such as linear and quadratic functions by using RSM to predict surface roughness and tangential force when turning AISI 1045 steel. Mansour et al.[5] studied a surface roughness model that utilizing RSM for milling steel in dry condition. Arbizu and Perez [6] presented a surface roughness prediction model using RSM to determine surface quality in turning processes. Choudhury and El-Baradie [7] developed surface roughness prediction model in turning of high strength steel by factorial design of experiments. Erzurumlu and Oktem [8] discussed the effect of cutting parameters on surface roughness. They developed RSM and an artificial neural network (ANN) model to predict surface roughness values error on mold surfaces. Ozel and Karpat [9] used regression and ANN for predictive modeling of surface roughness and tool wear in hard turning. Nalbant et al. [10] examined Taguchi method in the optimization of cutting parameters for surface roughness in turning. Davim [11] studied the influence of cutting conditions on the surface finish obtained by turning, based on the techniques of Taguchi.

In this study, The Design-Expert software package was used to develop RSM model and to apply the desirability approach. RSM with CCD was adopted to obtain an emprical model of surface roughness (response) as a function of cutting speed feed rate and depth of cut (input factors). The optimum process conditions were determined by using desirability functions. Desirability function is an attractive method for industry for optimization of quality characteristic problems.

## 2 EXPERIMENTAL DETAILS

The cutting experiments were carried out a Goodway GS-280 industrial type of CNC lathe. HSS tool ($\alpha = 8°$, $\gamma = 14°$, $r = 0.4$ mm) was used for the machining of AISI 4140 steel bars with cutting fluid. The mean surface hardness of samples was measured as 195 HB after normalizing at 870 °C The chemical compositions of AISI 4140 steel is given in **Table 1**.

**Table 1:** Chemical composition of AISI 4140 steel in mass fractions, *w*/%
**Tabela 1:** Kemična sestava jekla AISI 4140

| C | Mn | P | S | Si | Cr | Mo |
|---|---|---|---|---|---|---|
| 0.38–0.43 | 0.75–1.00 | 0.035 max | 0.040 max | 0.15–0.30 | 0.80–1.10 | 0.15–0.25 |

These bars of 30 mm diameter and 200 mm in length were prepared. Test samples were trued, centered and cleaned by removing a 1 mm depth of cut ($a_p$) from the outside surface, prior to actual machining tests. Three replications of each cutting conditions were conducted resulting in a total of 60 tests. A Mahr Perthometer-M1 type of portable surface roughness tester was used for measuring surface roughness. Input parameters of the models are cutting speed ($v_c$), feed rate ($f$) and depth of cut ($a_p$). Output parameter of the models is the corresponding surface roughness ($R_a$). Factors and levels for CCD) are given in **Table 2**. The relationship between the coded factors and the actual factors are shown in Equations 1-3.

$$x_1 = \frac{speed - (speed_{low} + speed_{high})/2}{(speed_{high} - speed_{low})/2} \tag{1}$$

$$x_2 = \frac{feed - (feed_{low} + feed_{high})/2}{(feed_{high} - feed_{low})/2} \tag{2}$$

$$x_3 = \frac{doc - (doc_{low} + doc_{high})/2}{(doc_{high} - doc_{low})/2} \tag{3}$$

where $x_1$ is the coded factor that represent the cutting speed, $x_2$ is the coded variable that represent the feed rate, $x_3$ is the coded variable that represent the depth of cut (doc).

**Table 2:** Factors and levels for CCD
**Tabela 2:** Faktorji in nivoji za CCD

| Factors/Levels | –1.68 | –1 | 0 | +1 | +1.68 |
|---|---|---|---|---|---|
| Cutting speed ($v_c$) | 16 | 47 | 92 | 137 | 167 |
| Feed rate ($f$) | 0.032 | 0.1 | 0.2 | 0.3 | 0.368 |
| Depth of cut ($a_p$) | 0.160 | 0.5 | 1 | 1.5 | 1.840 |

## 3 DATA ANALYSIS AND DISCUSSION OF RESULTS

The arrangement and the results of the 20 experiments carried out. Experimental and predicted surface roughness values for CCD are shown in **Table 3**. The results of the model is given in **Table 4**. Significance level ($\alpha$) was selected as 0.05. The valu of $p$ for the term of model is less than 0.05 indicates that the obtained model is considered to be statistically significant. This value ($p < 0.0001$) showed that, the quadratic model fits well to the experimental results.

**Table 3:** Experimental and predicted surface roughness ($R_a$) values for CCD
**Tabela 3:** Eksperimentalne in napovedane vrednosti za CCD

| Run | Cutting speed $v_c$ /(m/min) | Feed rate $f$ /(mm/r) | Depth of cut $a_p$/mm | Actual $R_a$/µm | Predicted $R_a$/µm |
|---|---|---|---|---|---|
| 1 | 47 | 0.1 | 0.5 | 1.60 | 1.64 |
| 2 | 137 | 0.1 | 0.5 | 2.20 | 2.24 |
| 3 | 47 | 0.3 | 0.5 | 2.47 | 2.66 |
| 4 | 137 | 0.3 | 0.5 | 2,14 | 2.14 |
| 5 | 47 | 0.1 | 1.5 | 1.91 | 2.00 |
| 6 | 137 | 0.1 | 1.5 | 1.77 | 1.68 |
| 7 | 47 | 0.3 | 1.5 | 2.84 | 2.90 |
| 8 | 137 | 0.3 | 1.5 | 1.40 | 1.46 |
| 9 | 16 | 0.2 | 1 | 2.62 | 2.44 |
| 10 | 167 | 0.2 | 1 | 1.70 | 1.74 |
| 11 | 92 | 0.032 | 1 | 1.67 | 1.67 |
| 12 | 92 | 0.368 | 1 | 2.48 | 2.34 |
| 13 | 92 | 0.2 | 0.160 | 2.51 | 2.40 |
| 14 | 92 | 0.2 | 1.840 | 2.17 | 2.14 |
| 15 | 92 | 0.2 | 1 | 2.72 | 2.68 |
| 16 | 92 | 0.2 | 1 | 2.74 | 2.68 |
| 17 | 92 | 0.2 | 1 | 2.64 | 2.68 |
| 18 | 92 | 0.2 | 1 | 2.70 | 2.68 |
| 19 | 92 | 0.2 | 1 | 2.51 | 2.68 |
| 20 | 92 | 0.2 | 1 | 2.74 | 2.68 |

**Table 4:** The results of the model
**Tabela 4:** Rezultati modela

| Source | Sum of Squares | d*f* | Mean Square | *F*-value | *p*-value |
|---|---|---|---|---|---|
| Linear | 1.23 | 3 | 0.41 | 2.44 | 0.102 |
| Quadratic | 1.47 | 3 | 0.35 | 2.81 | <0.0001 suggested |
| Cubic | 0.078 | 4 | 0.49 | 29.65 | 0.35 |

Quadratic regression equation was developed for predicting surface roughness ($R_a$) within selected experimental conditions using RSM. Regression equation can be expressed as follows.

$$R_a = 2.68 - 0.21X_1 + 0.20X_2 - 0.078X_3 - 0.21X_1^2 - \\ -0.24X_2^2 - 0.14X_3^2 - 0.28X_1X_2 - 0.23X_1X_3 \tag{4}$$

where $x_1$ is cutting speed ($v_c$), $x_2$ is feed rate ($f$), $x_3$ is depth of cut ($a_p$).

It is observed that cutting speed ($v_c$) and depth of cut ($a_p$) have negative influence, feed rate ($f$) has positive influence on the surface roughness ($R_a$). The surface roughness ($R_a$) of AISI 4140 steel decreased with increasing cutting speed ($v_c$) and depth of cut ($a_p$) whereas increased with increasing feed rate ($f$). The

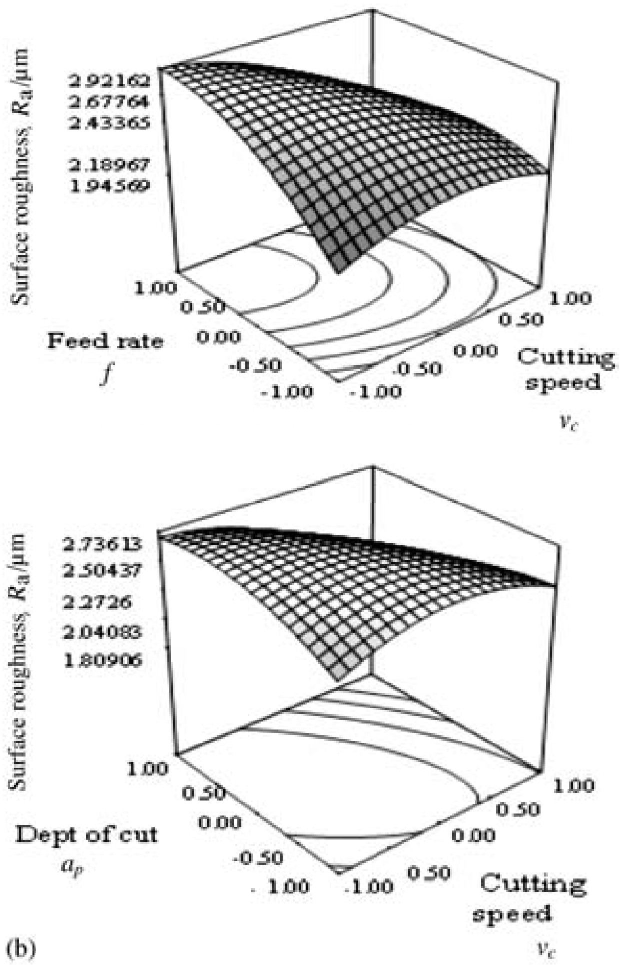


**Figure 1:** 3D response surface graphs for surface roughness ($R_a$)
**Slika 1:** 3D-graf odgovora za hrapavost površine ($R_a$)

**Table 5:** The ANOVA table for the quadratic model
**Tabela 5:** Anova tabela za kvadratičen model

| Source | SS | DF | MS | $F$-value | $p$-value |
|---|---|---|---|---|---|
| Model | 3.75 | 9 | 0.42 | 25.29 | < 0.0001 |
| $x_1$ | 0.60 | 1 | 0.60 | 36.29 | < 0.0001 |
| $x_2$ | 0.55 | 1 | 0.55 | 33.19 | < 0.0002 |
| $x_3$ | 0.0.83 | 1 | 0.083 | 5.01 | 0.0491 |
| $x_1^2$ | 0.62 | 1 | 0.62 | 37.72 | 0.0001 |
| $x_2^2$ | 0.81 | 1 | 0.81 | 49.43 | < 0.0001 |
| $x_3^2$ | 0.30 | 1 | 0.30 | 18.14 | 0.0017 |
| $x_1x_2$ | 0.62 | 1 | 0.62 | 37.74 | 0.0001 |
| $x_1x_3$ | 0.43 | 1 | 0.43 | 25.97 | 0.0005 |
| $x_2x_3$ | 0.007813 | 1 | 0.007813 | 0.47 | 0.5067 |

relationship between cutting speed ($v_c$) and feed rate ($f$) is shown in **Figure 1a**, the relationship between cutting speed ($v_c$) and depth of ($a_p$) is shown in **Figure 1b**.

It can be realized that the combination between high cutting speed and high feed rate ($f$) results in a considerable reduction in surface roughness ($R_a$) and also between high cutting speed ($v_c$) and high depth of cut results in a considerable reduction in surface roughness ($R_a$). The response surface plot (**Figure 1a**) indicates that the minimum surface roughness is at about 137 m/min and 0.3 mm/r. The response surface plot (**Figure 1b**) indicates that the minimum surface roughness is at about 137 m/min, and 1.5 mm.

An ANOVA table is commonly used to summarize the tests performed. It was statistically studied the relative effect of each cutting parameters on the surface roughness ($R_a$) by using ANOVA. The ANOVA table for response surface quadratic model for the surface roughness ($R_a$) is given in **Table 5**.

The value of $p$ is less than 0.05 indicates that the obtained model is considered to be statistically significant. Higher F value indicates that the variation of the process parameter makes a big changes on the surface roughness ($R_a$). As seen in **Table 5** cutting speed ($v_c$) and feed rate ($f$) is the most significant parameters, depth of cut ($a_p$) is the least significant parameter. All the

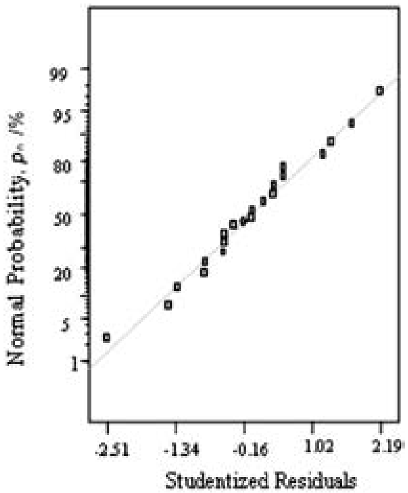


**Figure 2:** The normal probability plot of the residuals
**Slika 2:** Normalna verjetnost za reziduale

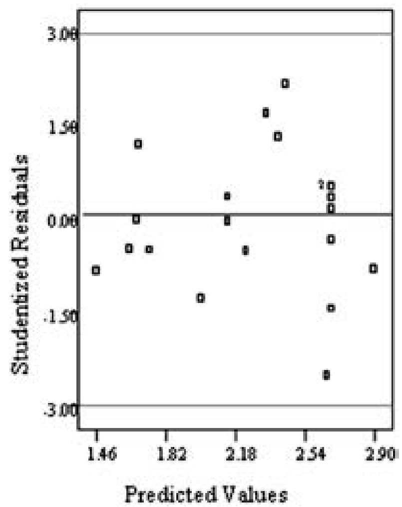


**Figure 3:** The standardized residual versus observation order plot
**Slika 3:** Standardni reziduali v odvisnosti od napovedanih vrednosti

squared terms and among interaction term cutting speed ($v_c$) – feed rate ($f$) and cutting speed ($v_c$) – depth of cut ($a_p$) appears to be highly significant.

We consider a measure of the model's overall performance referred to as the coefficient of determination and denoted by $R^2$. In the model, $R^2$ is obtained equal to 95 %. The $R^2$ value indicates that the cutting parameters explain 95 % of variance in surface roughness ($R_a$). The normal probability plot of the residuals is shown in **Figure 2**.

The predicted values were found to be statistically similar to the actual measured values, based on the plotted probability plot. **Figure 2** shows that the residuals generally fall on a straight line implying that the errors are distributed normally. The standardized residual versus observation order plot, as shown in **Figure 3**. It shows that the model proposed is adequate.

After building the regression model, a numerical optimization technique using desirability functions can be used to optimize the response. The objective of optimization is to find the best settings that minimize a particular response [12]. **Table 6** shows five alternative solutions of the optimization approach used to determine the optimum processing conditions. A desirability value, where $0 \leq d \leq 1$. The value of $d$ increases as the "desirability" of the corresponding response increases. The factor settings with maximum desirability are considered to be the optimal parameter conditions.

**Table 6:** Alternative solutions of optimum conditions
**Tabela 6:** Alternativne rešitve za optimalne pogoje

| Solutions | Cutting speed $v_c$ /(m/min) | Feed rate $f$ / (mm/r) | Depth of cut $a_p$ /mm | $R_a$/μm | Desirability (d) |
|---|---|---|---|---|---|
| 1 | 137 | 0.3 | 1.5 | 1.46 | 0.957 |
| 2 | 47 | 0.1 | 0.5 | 1.63 | 0.835 |
| 3 | 137 | 0.26 | 1.5 | 1.64 | 0.830 |
| 4 | 47 | 0.1 | 1.5 | 2.00 | 0.580 |
| 5 | 137 | 0.3 | 0.67 | 2.10 | 0.509 |

**Table 6** revealed that highest desirability could be obtained at high level of cutting speed, feed rate and depth of cut. Five different desirable ranges of input parameters and response which gives high value of desirability are shown in the table. These are the optimal conditions to obtain high value of desirability. The achieved maximum desirability of 0.957 means that it is possible to meet surface roughness ($R_a$) target. The lowest value of surface roughness ($R_a$) obtained is $R_a$ = 1.46μm at a cutting speed of $v_c$ = 137 m/min, a feed rate of $f$ = 0.3 mm/r and a depth of cut of $a_p$ =1.5 mm.

## 4 CONCLUSION

In this study, a quadratic model was developed for the prediction and analysis of the relationship between the cutting parameters and surface roughness ($R_a$) in turning process of AISI 4140 steel. It was observed that significance of the main variables is cutting speed ($v_c$) and feed rate ($f$). The comparisons of experimental results with the RSM predictions have been depicted in terms of percentage absolute error. In the prediction of surface roughness ($R_a$) values the average absolute errors for RSM is found to be as 3.18 %. This value is sufficiently low to confirm the high predictive power of model. Experimental results show that, it can be inferred that prediction models can be applied to determine the appropriate cutting conditions, in order to achieve specific surface roughness ($R_a$).

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