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RSM-BASED SURFACE ROUGHNESS MODELLING DURING AISI-H13 SLOT MILLING

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Abstract: *Surface roughness is a critical parameter when considering machining cost, tool longevity and mechanical component performance. A widely applied method for developing prediction models is Response Surface Method (RSM). In the present work, RSM was implemented to facilitate the development of a model for prediction purposes of surface roughness during AISI-H13 slot milling. 30 experiments were prepared and carried out with the aid of a machining center, according to the Central Composite Design (CCD). Surface roughness was measured on multiple points on each slot and an average value was calculated for both Ra and Rz. The results of the study indicated a strong correlation between the experimental and the predicted measurements, with levels of agreement exceeding 85% in most cases.*

Key words: *Surface roughness, RSM, Central composite design, AISI-H13, Slot milling, ANOVA.*

1. INTRODUCTION

Whether conventional or non-conventional machining is used for the production of a part, surface roughness remains a key factor that indicates the quality of the machined part, as well as the process effectiveness. Therefore, accurate measurement and predictive modelling of the surface roughness is important to most manufacturing industries. Many researchers have dealt with the investigation of surface roughness as a result of its importance in the industry.

Benardos and Vosniakos [1] implemented Artificial Neural Networks (ANN) and Design of Experiments (DOE) in their work to develop a predictive model for surface roughness during face-milling of aerospace aluminium alloy. Özel et al. [2] investigated the effects of the tool nose radius on the surface integrity and the tool wear, when hard turning AISI-D2 steel. The authors used multiple regression models and ANN for the prediction of the investigated parameters.

Similarly, Mia and Dhar [3] utilized ANN for the surface roughness modelling during hard turning of EN 24T steel, under high pressure coolant. Asiltürk and Akkuş [4] examined the effect of cutting parameters on the surface roughness generated during AISI-4140 dry machining. The authors used the Taguchi method to design the experiments and the Response Surface Methodology (RSM) to identify the effects of feed, cutting speed and depth of cut on the surface roughness.

Hua and Liu [5] studied the effects of the cutting conditions and the tool nose radius on the surface roughness and the work hardening of Inconel 718 during dry cutting. Meddour et al. [6] utilized the RSM to model the surface roughness and the cutting forces generated during hard turning of AISI52100 steel with ceramic tools.

The authors used the Central Composite Design (CCD) to carry out the designing of the experimental work, as well as to maintain the number of the tests to a reasonable level.

The present paper deals with the development of a predictive model for the surface roughness for slot milling AISI-H13 steel. A DOE was carried out to generate the ideal, for this case, combinations of experiments and RSM was utilized to examine the effect of each of the factors applied. Despite the fact that a high number of surface roughness prediction models exist in the literature, most of the time only three parameters are taken into account, leaving depth of cut or tool diameter out of the equation.

This work, presents a broader model, involving four cutting parameters at three levels, by implementing the CCD, in contrast to more standardized statistical methods used in the majority of similar studies.

2. MATERIAL AND METHODS

2.1 Experimental design

To examine the effects of the cutting conditions, as well as their interaction in a designed environment, the experimental cuts were carried out according to the CCD, which is a method implemented in machining [6] investigations, especially when a large number of experimental testing is involved. The cutting conditions that were investigated are the cutting speed, the feed, the depth of cut and the tool diameter. Table 1 includes the parameters and their corresponding levels.

Table 1

Cutting conditions and their levels.

Levels	V_c (m/min)	f (mm/rev)	a_p (mm)	D (mm)
+1	190	0.26	1.5	10
0	175	0.22	1.0	8
−1	160	0.18	0.5	6

The selection of the cutting condition values was done according to the tool manufacturer's recommendations for the machining of the chosen test piece made out of AISI-H13 (DIN 1.2344) ultra-high strength steel, which is considered to be one of the best choices for many industries since it provides excellent machinability and constant hardness during production processes.

Machining of steels is a topic which is extensively studied due to the increased usability of these materials by the industry. AISI-52100, AISI-4140 and AISI-D2 are indicative types of steel, used for the production of tools, bearings, and engine parts, that has been studied with various methods such as soft computing and numerical methods [7–9]. Table 2 contains the most basic physical and mechanical properties of the AISI H13 tool steel.

Table 2

AISI-H13 properties.

Density (kg/m^3)	7870
Poisson's ratio	0.29
Modulus of elasticity (GPa)	200
Bulk modulus (GPa)	140
Shear modulus (GPa)	80

Figure 1 illustrates the geometrical aspects of the used tools.

Three diameters were chosen, 6 mm, 8 mm and 10 mm with identification numbers SM3415.060.G00, SM3415.080.G00 and SM3415.100.G00 respectively. These tools are coated, flat end-mills with z=3, 45° chamfered corner and variable helix of 45° and 48°.

Based on the number and the levels of the cutting conditions, the total number of the tests is equal to 3^4.

The Box-Wilson CCD comprising of 16 factorial points, 4 center points, 8 axial points, 2 axial center points and α=1, reduced the number of tests to 30. The use of a factorial design is common when multiple parameters participate in the study and the tests are time- and resource-consuming.

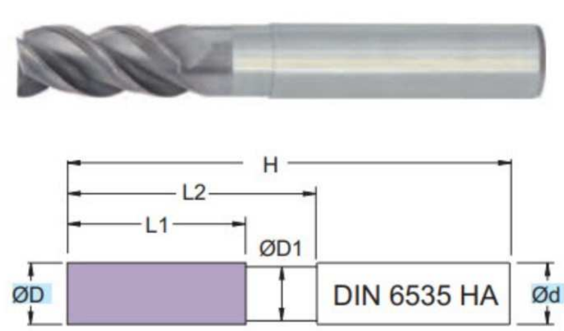

Fig. 1. The geometrical characteristics of the end-mills.

2.2 Experimental framework

The selected test piece was a disk with 250 mm diameter and 44.5 mm thickness (Fig. 2a). As shown in figure 2a, each slot was cut with an equal length and according to the order and the conditions defined by the DOE (see Table 3 in section 3.1). In addition, they were numbered for reference. Surface roughness was measured on multiple single paths on each slot, with the aid of a TESA™ Rugosurf 20 surface roughness tester (Fig. 2b). Then, the average surface roughness was recorded for both R_z and R_a.

According to many well-known surface roughness and profile gauge manufacturers, the arithmetic mean R_a and the individual roughness depth R_z are the most important parameters when evaluating the surface texture of a machined part. This fact is supported by the DIN EN ISO 4287 standard, which deals with the surface texture of products.

Fig. 2. The experimental setup: the round test piece (a) and the roughness gauge (b).

Finally, the experimental testing was performed on a MAZAK™ VCN-530C vertical machining center. It is noted that both sides of the test piece were used and only one set of tools was used for the machining experiments to reduce the expenses. However, the coating of the tools and the small length of cut ensured that the tool wear influence on the surface roughness was negligible.

3. RESULTS

3.1 Surface roughness model development

The RSM constitutes a well-established tool for mathematical modelling and evaluation of multiple independent variables, implemented by a number of studies in machining [6,10,11]. Moreover, it can be used for the visualization of results that involve the interaction of several factors.

In this case, RSM was utilized to carry out the design of the experimental process, evaluate the interaction between the applied cutting parameters and develop the mathematical model for the surface roughness.

Table 3 presents the total number of the experimental tests according to their run order and the combinations of the cutting parameters, in addition to the results for the surface roughness in terms of R_a and R_z.

Table 3

The experimental tests and the recorded surface roughness values.

Run order	V_c (m/min)	f (mm/rev)	a_p (mm)	D (mm)	R_a (μm)	R_z (μm)
1	160	0.18	0.5	10	0.621	3.894
2	190	0.18	1.5	10	0.951	5.136
3	190	0.26	1.5	10	1.344	7.615
4	160	0.18	1.5	6	2.969	11.786
5	160	0.18	1.5	10	1.365	6.117
6	190	0.18	0.5	6	1.335	6.017
7	175	0.22	1.0	8	2.215	10.179
8	190	0.26	0.5	6	3.279	11.483
9	160	0.26	1.5	10	1.370	7.086
10	190	0.26	1.5	6	2.881	12.382
11	160	0.26	0.5	10	0.923	4.358
12	160	0.18	0.5	6	1.462	6.658
13	190	0.18	1.5	6	2.242	9.532
14	190	0.26	0.5	10	1.169	5.458
15	175	0.22	1.0	8	2.411	10.666
16	175	0.22	1.0	8	2.223	9.567

17	190	0.18	0.5	10	0.268	3.126
18	160	0.26	1.5	6	3.150	11.832
19	175	0.22	1.0	8	2.040	9.245
20	160	0.26	0.5	6	2.998	11.039
21	175	0.22	0.5	8	2.425	9.865
22	175	0.26	1.0	8	2.896	10.972
23	175	0.22	1.0	10	0.786	5.459
24	175	0.22	1.0	8	2.382	9.864
25	175	0.22	1.0	6	1.988	9.020
26	160	0.22	1.0	8	2.956	11.899
27	175	0.18	1.0	8	1.785	9.464
28	190	0.22	1.0	8	2.332	10.730
29	175	0.22	1.5	8	2.601	12.971
30	175	0.22	1.0	8	2.223	8.896

Equation 1 can be used to examine the relationship, as well as the interaction between the input parameters. It is a second order polynomial that expresses the response with respect to the inputs. Hence, Y is the response (R_a and R_z for this case), a_0 a constant, b_i, b_{ii} and b_{ij} represent the first and second order coded input parameters and the interaction between the parameter's coefficient respectively. Finally, X_i and X_j denote the equivalent variables (cutting parameters).

$$Y = a_0 + \sum_{i=1}^{n} b_i X_i + \sum_{i,j}^{n} b_{ij} X_i X_j + \sum_{i=1}^{n} b_{ii} X_i^2 \quad (1)$$

Equations 2 and 3 represent the models for the surface roughness after the backward elimination was applied.

Due to the high number of the parameters that participate in the regression, it was necessary to identify the variables and their interactions that deteriorate the model's fitting line.

In other words, any factor with insignificant degree of influence on the model or with deteriorating effect was removed. This way, the model was simplified, its performance was improved, and over-fitting was avoided.

$$R_a = 37.8 - 0.593V_c + 5.01a_p + 3.688D + 0.001576V_c^2 - 0.2256D^2 + 0.2111V_c \times f - 0.01236V_c \times a_p - 10.73f \times a_p - 2.062f \times D \quad (2)$$

$$R_z = -30.73 - 0.1305V_c + 13.40D + 3.514a_p^2 - 0.8320D^2 + 0.539V_c \times f - 20.56f \times a_p - 5.64f \times D \quad (3)$$

3.2 Model validation

To examine the effectiveness of the model, specifically the statistical significance of the models, as well as the lack of fit, and identify the reactive and non-reactive effects of the cutting conditions, the Analysis of Variance (ANOVA) was utilized with the confidence level set to 0,05.

Table 4 and 5 contain the ANOVA results for R_a and R_z accordingly. Where DF is the degrees of freedom of each term and SS denotes the sum of squares. It is noted that the total value of the sum of squares includes the values of the rest of the terms, which were not included in the model.

An examination of the p-value of each of the factors, revealed their significance. Every factor with a p-value lower than the confidence level, which is equal to 0.05, has an increased contribution. Therefore, all terms with the exception of $V_c \times a_p$ contribute the most to the predicted R_a.

Table 4

ANOVA results for R_a parameter.

Source	DF	SS	f-value	p-value
V_c	1	0.4991	13.71	0.000
a_p	1	0.6037	16.59	0.001
D	1	2.6755	73.51	0.000
V_c^2	1	0.4332	11.90	0.003
D^2	1	2.8047	77.06	0.000
$V_c \times f$	1	1.9299	53.02	0.000
$V_c \times a_p$	1	0.1375	3.78	0.066
$f \times a_p$	1	0.7568	20.79	0.000
$f \times D$	1	0.4848	12.32	0.002

error	20	0.7280		
total	29	19.8880		
R^2=96.34% - $R^2_{adjusted}$=94.69% - $R^2_{predicted}$=91.09%				

Table 5

ANOVA results for R_z parameter.

Source	DF	SS	*f*-value	*p*-value
V_c	1	12.979	22.23	0.000
D	1	54.177	92.79	0.000
a_p^2	1	9.167	15.70	0.001
D^2	1	60.577	103.75	0.000
$V_c \times f$	1	13.225	22.65	0.000
$f \times a_p$	1	3.866	6.62	0.017
$f \times D$	1	3.626	6.21	0.021
error	22	12.845		
total	29	223.595		
R^2=94.26% - $R^2_{adjusted}$=92.43% - $R^2_{predicted}$=89.42%				

Similarly, the only terms that do not affect R_z significantly, are the $f \times a_p$ and the $f \times D$.

On the other hand, the *f*-value was used to identify the contribution percentage of the terms. D, D^2 and $V_c \times f$ are the terms with the highest level of influence on R_a, yielding 26%, 27.26% and 18.75% accordingly. D and D^2 are the most effective parameters for R_z with a contribution percentage equal to 34.37% and 38.43% respectively.

The levels of the *R*-square values indicate a strong fit for both models. Moreover, the adjusted and the predicted *R*-square values suggest that the quantity of the model terms is sufficient and that the model can yield predicted values of the surface roughness with adequate reliability within the specified range of cutting parameters.

To validate the aforementioned statements, the normal probability plot for each model was plotted and investigated, as well as the comparison graph between the experimental and the predicted values of surface roughness. In specific, by observing the normal probability plots of figure 3 it is pointed out that there are no evident point departures from the fit line. Figure 3a illustrates a good fit for R_a, with the exception of a small number of points located between 0.1 and 0.2 residuals.

A similar pattern is observed in figure 3b for R_z, proving the goodness of fit. To further validate the modelling reliability, the generated surface roughness models were used to calculate the predicted values in order to compare them with the experimental ones.

To do so, a comparison graph was plotted.

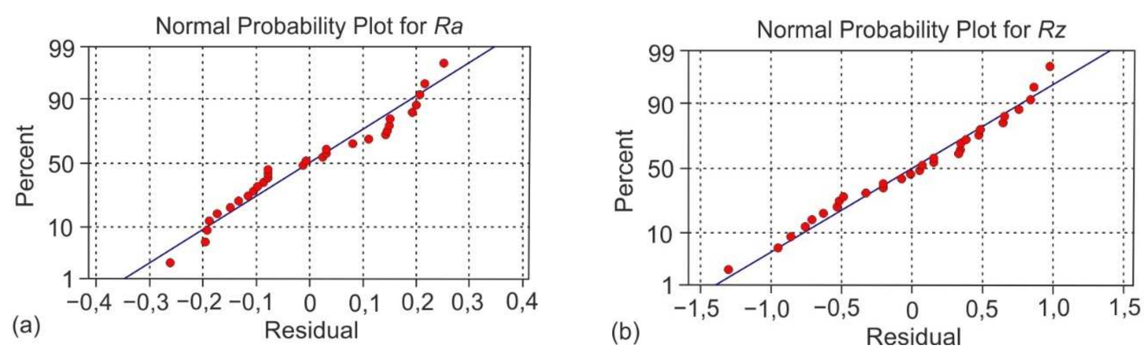

Fig. 3. The normal probability plot for R_a (a) and R_z (b).

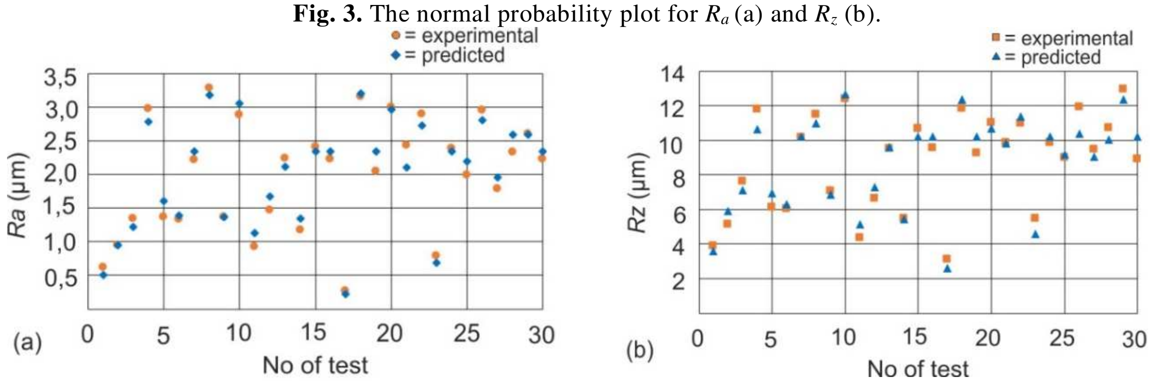

Fig. 4. Comparison between experimental and predicted values of R_a (a) and R_z (b).

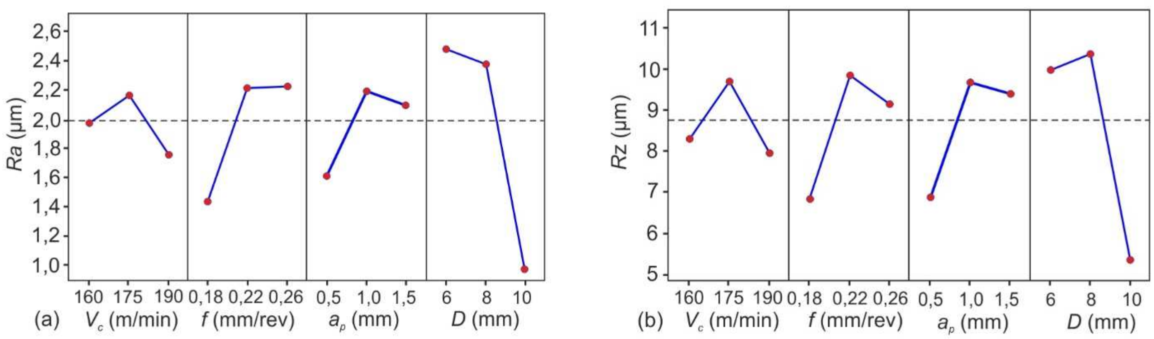

Fig. 5. The main effects plot for R_a (a) and R_z (b).

Figure 4 depicts the aforementioned graph, indicating an increased correlation between the experimental and the statistically generated results.

Moreover, the relative error for R_a ranges from −22.2% to 19.1%, with the majority of the values falling at the range between −5.8% and 6.5%. Similarly, the relative error for R_z was found to be between −18.3% and 17.3%, with most values being within the −6.6% and 6.6% limits.

3.3 Variable effects evaluation

The visualization of the variable effects was achieved with the main effects plot (Fig. 5), which is considered to be a simple graphical tool for the comparison of the changes in the means and for the identification of the variable influence on the response.

Figure 5a and 5b illustrate the individual impact of the four cutting parameters on the R_a and R_z respectively.

It is evident that the tool diameter contributed the most to the surface roughness values. On the contrary, cutting speed had a lighter effect.

Additionally, the influence of feed and depth of cut was similar. Specifically, the lower values of feed and depth of cut aided in the generation of better surface quality. On the contrary, the middle values were responsible for higher values of surface roughness.

Moreover, the middle values of every parameter contributed to the development of the highest surface roughness profiles. Finally, the tool diameter equal to 10 mm had the best positive impact to the surface roughness development.

4. CONCLUSION

Concluding, this paper presented a statistically based predictive model for the surface roughness produced for slot-milling AISI-H13 high-strength steel.

The RSM coupled with ANOVA were utilized to develop, as well as to verify the model. By completing this study, the following remarks can be made.

- The model can generate predicted values for the surface roughness with increased reliability and accuracy within the scope of this study.
- Tool diameter and some of its combinations are the terms that affect the most the response of the model.
- The Ø8 tool has a negative impact on the produced surface quality. In contrast, the Ø10 tool seems to greatly affect the surface roughness in a beneficial manner.
- Finalizing, it is evident that individually, a value of 190 m/min speed, 0.18 mm/rev feed, 0.5 mm depth of cut, and the Ø10 tool can contribute to the generation of smoother surfaces.

5. ACKNOWLEDGMENTS

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MODELAREA RUGOZITĂȚII SUPRAFFEȚEI UTILIZÂND RSM LA FREZAREA FANTELOR IN EPRUVETE DIN OȚEL AISI-H13

Rugozitatea suprafeței este un parametru critic atunci când se ia în considerare costul prelucrării, durabilitatea sculei și performanțele de utilizare ale componentelor mecanice. O metodă aplicată pe scară largă pentru dezvoltarea modelelor de predicție este metoda suprafeței de răspuns (RSM). În lucrarea de față, RSM a fost folosită pentru a facilita identificarea unui model de predicție a rugozității suprafeței la frezarea fantelor în semifabricate din oțel AISI-H13 (DIN 1.2344). Un set de 30 de experimente a fost planificat și realizat pe un centru de prelucrare vertical MAZAK, în concordanță cu cerințele unui program compozit central (CCD), fiind astfel posibilă implicarea a patru parametri de așchiere, în loc de trei parametri ai regimului de așchiere, parametri care sunt de obicei luați considerare. S-a ținut cont de viteza de așchiere, de avans, de adâncimea de așchiere și de diametrul sculei, cu trei niveluri de variație, iar influența lor a fost reprezentată grafic, sub forma graficului efectului principal. Rugozitatea suprafeței a fost măsurată în mai multe puncte ale fiecărei fante și a fost calculată o valoare medie, atât pentru parametrul Ra, cât și pentru parametrul Rz. În cele din urmă, adecvanța modelului stabilit a fost evaluată folosind analiza varianței (ANOVA). Rezultatele studiului au indicat o corelație puternică între rugozitatea suprafeței măsurată pe cale experimentală și cea prezisă, cu niveluri de concordanță depășind 85% în majoritatea cazurilor.

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