

Mathematical Methods of Surface Roughness Evaluation of Areas with a Distinctive Inclination

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Surface roughness is one of the most significant evaluation factor in metal machining operations. Despite the small descriptiveness is usually quantified as the arithmetical mean roughness R_a especially in the automotive industry. In order to maintain the desired surface roughness, the appropriate setting of machining parameters is important to be set before the actual cutting process. The objective of this research is to analyse the effect of machining parameters on surface roughness of stainless steel X153CrMoV12-1 in CNC milling of slope surfaces with sintered carbide tool. The data were processed using multiparametric statistical methods to find optimal results. Linear regression models and probability dendrograms of similarities were determined for cutting conditions, cutting tools and slope of machined surfaces.

Keywords: CNC Milling, Cutting Tool, Multiparametric Statistical Methods, Surface Roughness, Surface Slope.

1 Introduction

Injection molds, die-casting and die-forging molds together with stamping tools are used in mass production of identical parts in huge quantity often for the automotive and consumer industry. The manufacture requires precise and accurate production process since the imperfections are replicated into the final product. For this reason, the production process is analysed during manufacture, computer numerical controlled (CNC) machines are employed to ensure a high repeatability and predictability of production. Resulting mold or tool surface quality is directly linked to finish machining operations whereat ball end milling methods on CNC machine tools are applied. The mill tool with ball end makes sense to use mainly for milling of complex inclined surfaces. That usage will prevent known phenomenon where the resultant speed near the axis of the tool is very close to zero and at such a place, the material is not machined.

Surface roughness is one of the parameters with great importance considered for the functional behaviour of the mold or tool, moreover is widely used as a description of surface quality and as a technical requirement in most cases [1, 2] of mechanical engineering. In general, milling is a highly complex process influenced by a large number of factors among interacting [3-9]. Accordingly, the resulting surface roughness and its formation is affected by cutting conditions, cutting tool properties, workpiece properties, cutting phenomena [10, 11] and part program accuracy [12].

Prediction of surface roughness includes various approaches from simple kinematic models [13], over complex methodology evaluation with more input parameters [14-24] using artificial neural networks (ANN), response surface methodology (RSM), artificial intelligence (AI), multiple regression or fuzzy modelling. Despite a number of methods, surface roughness models describe the behaviour with limiting boundary conditions for the specific case only. Recalculation according to the desired surface roughness can give machining conditions outside the

working range of the machine tool or on the contrary require settings of machining conditions with high sensitivity.

In this research is analysed the probability of R_a parameter similarities of machining conditions, especially feed, if can be set at a certain interval without resulting surface roughness was significantly changed. This would allow the less robust control systems to be used. Moreover, article focuses on the question of whether it is worth to use cutting tools with different geometries for areas with a distinctive inclination. Solution includes the application of multiparametric statistical methods and determination of linear regression models.

2 Experimental details

The machining parameters selected for this experiment were given as recommended by the tools manufacturer for the workpiece material. Input values of the machining were radial depth of cut a_e , feed f_z , surface inclination angle α and tool rake angle γ while the spindle speed remains constant at 5308 RPM (in Tab. 1). Workpiece material was stainless steel X153CrMoV12-1 with 63 of Rockwell Hardness, generally used in molds and tools manufacturing.

The milling operations were performed on three axes vertical CNC milling centre Mikron HSM 800. For the purpose of the experiment were selected ball end mill tools from sintered carbide with PVD coating. Whereas each of tool geometry parameters were unchanged, only tool rake angle (Fig. 1 right) was different, hereinafter referred to as positive geometry was the tool with 12° , while the tool with negative geometry was -4° of rake angle. Generally, positive geometry is suitable for machining of steel and cast iron parts prone to vibration, but also for workpieces of aluminium alloys and super alloys that easily form build-up edge. Negative geometry is suitable for milling steel, cast iron and hard to machine materials that ensures prolonged tool life nevertheless require higher cutting power [25, 26]. As the tool clamping unit was used the shrink fit holder HSK 50E on a modular system Easyshrink 20. The overhang of the tool in the tool holder

was 50 mm.

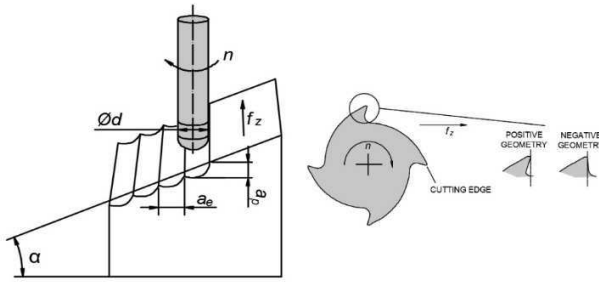


Fig. 1 Scheme of machining process (left) with positive and negative tool geometry of tool rake angle (right)

Powermill software was used to create part program for CNC milling within the ± 0.01 mm tolerance, using Constant Z strategy. The feed direction was parallel to y axis of the machine tool (see Fig. 1 left) and climb cutting strategy was chosen for the better surface roughness. The

part program was checked before manufacturing in internal verification by Powermill software and potential errors and collisions were debugged. The oil mist Unicut-EP-A4 was used for cooling in the rate of 1:500000 to air during milling. A surface of the workpiece in the range of $0^\circ - 30^\circ$ is referred to as shallow, and therefore the angle of inclination $\alpha = 15^\circ$ are hence denoted. Conversely, in areas ranging from $30^\circ - 90^\circ$ have been described as steep, and we do so for the workpiece surface inclination $\alpha = 75^\circ$.

Measurements were carried out using surface roughness tester Mitutoyo SJ-301 according to ISO standards. Surface roughness was measured in the direction perpendicular to the feed repeatedly 30 times on machined surface. For this reason, was necessary to applicate in the paper multiparametric statistical methods to find optimal result. In the paper was used finding and testing linear regression models and dendrogram graphs to demonstrate probability of similarity R_a parameter for tool with positive and negative geometry.

Tab. 1 Machining conditions

Tool geometry	Negative	Positive
Spindle speed (n)	5308 RPM	5308 RPM
Radial depth of cut (a_e)	0.16 - 0.25 - 0.32 - 0.40 - 0.60 mm	0.16 - 0.25 - 0.32 - 0.40 - 0.60 mm
Axial depth of cut (a_p)	0.5 mm	0.5 mm
Feed per tooth (f_z)	0.1 - 0.12 - 0.135 - 0.15 - 0.17 mm	0.1 - 0.12 - 0.135 - 0.15 - 0.17 mm
Surface inclination angle (α)	15° and 75°	15° and 75°
Tool rake angle (γ)	-4°	12°
Tool diameter (d)	12 ± 0.01 mm	12 ± 0.01 mm

3 Results and discussion

The following are the results for milling with the radial depth of cut $a_e = 0.40$ mm. Other measurements were similar behaviour, and thus omitted. As described below it is large problem to specify which of the tools is better to use for shallow surfaces or for steep surfaces.

3.1 Shallow surfaces

In the diagram (Fig. 2) is implied cause of the problem. E.g. at feed $f_z = 0.17$ mm for negative geometry and $f_z = 0.1$ mm positive geometry cannot be statistically by using appropriate tests rejected the equality of mean values expressed by the arithmetic means.

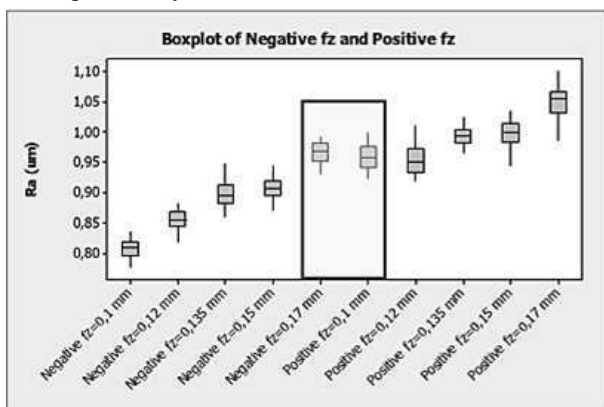


Fig. 2 Surface roughness of shallow surfaces for positive and negative tool geometry

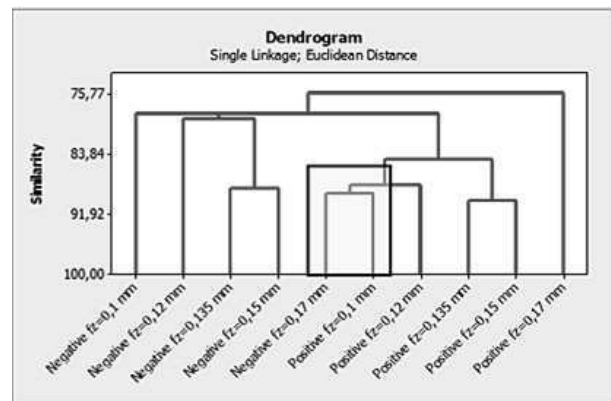


Fig. 3 Data similarity analysis

This problem then led to the idea that the tool geometry (positive, negative) during milling shallow surfaces do not matter, which as discussed below, is incorrect hypothesis. The dendrogram in the Fig. 3 marked a similarity of results for both the positive and negative geometry. Mentioned $f_z = 0.17$ mm for negative geometry and $f_z = 0.1$ mm for positive geometry is indicated by a frame. From dendrogram follows that the similarity of R_a values for both positive and negative geometry at different values of f_z is high (i. e., approaching a value of 80 percent). This means that in general parameter R_a and feed f_z is not a prominent difference between whether the tool with positive or negative geometry was used.

It can be concluded that the measured values of R_a parameter for geometry of both positive and negative for

the above-defined values f_z are derived from a normal distribution, contain no misleading outlier Ra values and do not show the autocorrelation of up to 4th order.

As the next step data transformation is performed, which should result in the stabilization of the possible variance of Ra values, respectively to his symmetrisation. From the graph of the logarithm of the credibility function was seen that the interval of the parameter λ , which was designed for the $1-\alpha = 0.95$ includes the value 1, which implies that the Box Cox transformation is not significant as well as transformation.

Tab. 2 Mean values of Ra

Conditions:	Negative, $f_z = 0.17$ mm	Positive, $f_z = 0.1$ mm
Mean	0.9651	0.9594
Median	0.9670	0.9565
Retransformed mean by Box Cox transformation	0.9629	0.9571
Retransformed mean by power transformation	0.9672	0.9570

Tab. 3 Statistical characteristics of regression

Tool geometry:	Negative	Positive
Multiple correlation coefficient:	0.9888	0.9432
Coefficient of determination:	0.9777	0.8896
The predicted correlation coefficient:	0.9037	0.3115
Root mean square error of prediction:	0.0001	0.0006
Akaike information criterion:	-44.0828	-40.2987
The residual sum of squares:	0.0003	0.0007
Mean of absolute residues:	0.0063	0.0113
Residual standard error:	0.0105	0.0154
Residual variance:	0.0001	0.0002
Skewness residues:	0.4125	0.0700
Kurtosis residues:	2.3703	1.2841

From the Tab. 2 is apparent that mean values of Ra start to diverge on the third decimal place; mean of Ra will be used as the characteristic estimation value.

Next, was used theory of hypothesis, namely F-test and two tail t-test for evaluating the estimation of arithmetic averages of Ra , obtained by the tool with positive and negative geometry under former mentioned f_z values.

Hypothesis for F-test was

$$H_0: \sigma_{Ra \text{ Negative } f_z=0.17 \text{ mm}}^2 = \sigma_{Ra \text{ Positive } f_z=0.1 \text{ mm}}^2$$

H_a : NON

where $1-\alpha=0.95$

Based on the above values we can conclude that H_0 hypothesis of equality of Ra means for positive and negative geometry of the specific values f_z cannot be rejected. Practically, this means that Ra values for positive and

negative tool geometry for given f_z do not detect the influence of geometry and feed. It could therefore lead to the consideration that when milling shallow surfaces is not important the tool geometry. In this manner was examined more similarities with a comparable result. For this reason, we proceed via regression analysis and finding the estimates of linear regression parameters.

As is mentioned in the Tab. 3, it is possible to say that the models for positive and negative geometry are significant and correct, residues indicated homoscedasticity and are normally distributed, and autocorrelation is insignificant.

3.2 Steep surfaces

In the steep surfaces is possible to say that is not difficult to find differences between tool with positive and negative geometry. There is a great difference between Ra parameter as is shown in the box plot diagram and dendrogram too (see Fig. 4-5). But it is necessary to propose the regression model and make its testing, as is mentioned below.

It is possible to say that multiple correlation coefficient, coefficient of determination and the predicted correlation coefficient are high and skewness and kurtosis of residues are close to normal distribution. From regression triplet in Figure 6 and for equation for (3) a (4) is possible to say that model of regression is significant, correct, residuals indicate homoscedasticity and there is not autocorrelation in the data.

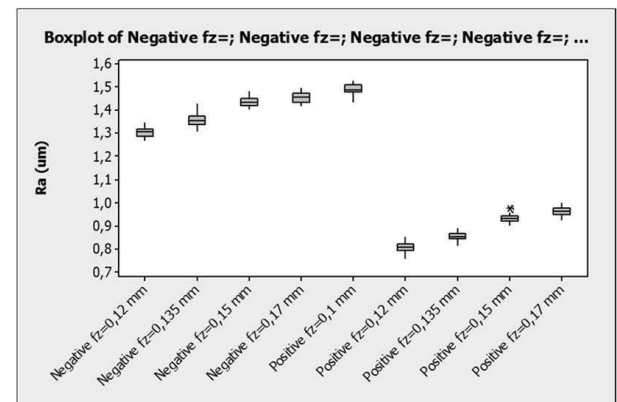


Fig. 4 Surface roughness of steep slope surfaces for positive and negative tool geometry

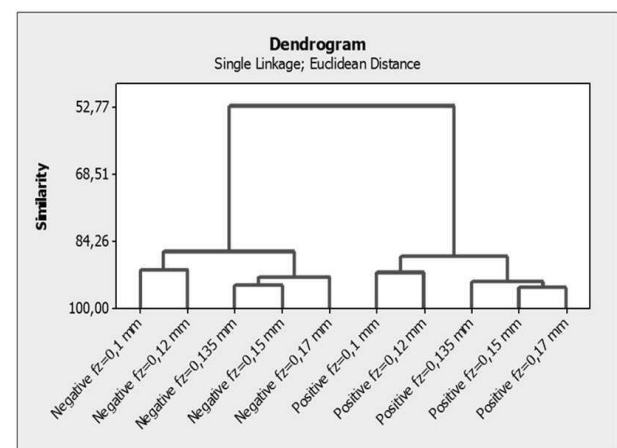


Fig. 5 Data similarity analysis of steep slope surfaces

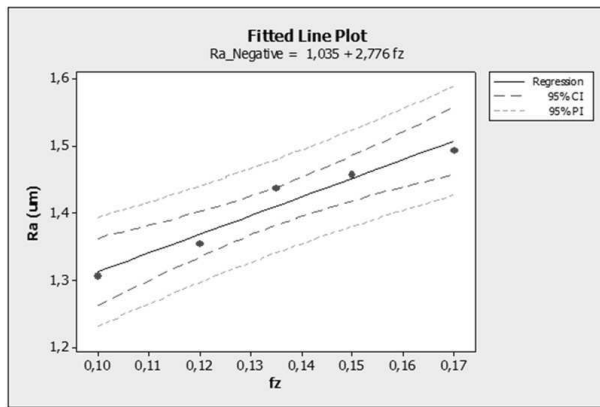


Fig. 6 Linear regression for negative tool geometry

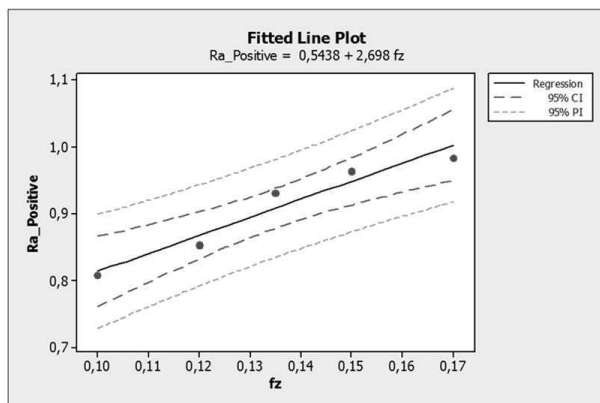


Fig. 7 Linear regression for positive tool geometry

Tab. 4 Statistical characteristics of regression

Tool geometry:	Negative	Positive
Multiple correlation coefficient:	0.9742	0.9699
Coefficient of determination:	0.9491	0.9407
The predicted correlation coefficient:	0.7446	0.6580
Root mean square error of prediction:	0.0006	0.0008
Akaike information criterion:	-37.6828	-37.1635
The residual sum of squares:	0.0012	0.0013
Mean of absolute residues:	0.0133	0.0153
Residual standard error:	0.0200	0.0210
Residual variance:	0.0004	0.0004
Skewness residues:	0.6906	0.1022
Kurtosis residues:	2.2222	1.4030

3.3 Chow test of shallow and steep surfaces

In case of shallow surfaces should be considered regression equations as follows:

$$Ra_{negative\ geometry} = 0.5839 + 2.244 \times f_z [\mu m] \quad (1)$$

$$Ra_{positive\ geometry} = 0.8008 + 1.404 \times f_z [\mu m] \quad (2)$$

Considering zero and alternative hypothesis and Chow test we have obtained

$$H_0: \beta_{Ra\ negative\ geometry} = \beta_{Ra\ positive\ geometry}$$

$$H_a: \beta_{Ra\ negative\ geometry} \neq \beta_{Ra\ positive\ geometry}$$

on the confidential level $1 - \alpha = 0.95$.

Criterion of the test for case of homoscedasticity and number of freedom:

$$RSC\ negative = 333.08E-5$$

$$RSC\ positive = 709.97E-5$$

$$RSC\ positive + negative = 2884.30E-5$$

$$F_{ch} = 80.02$$

$$F_{0.95} (m=2, n-2*m=6) = 5.14$$

It is possible say that $F_{0.95} = 5.14 < F_{ch} = 80.02$ and then it is possible to reject zero hypothesis that regression equations (1) and (2) are equal and differences Ra on the shallow surface area are randomize only. Practically is possible to say that there is statistically significant difference between tools with positive and negative geometry for machining shallow surface.

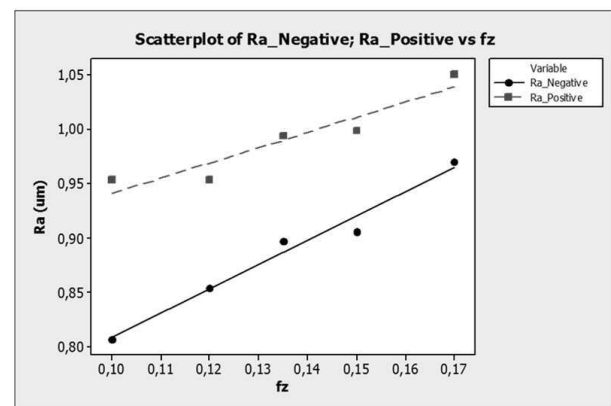


Fig. 8 Surface roughness correlations for shallow surface

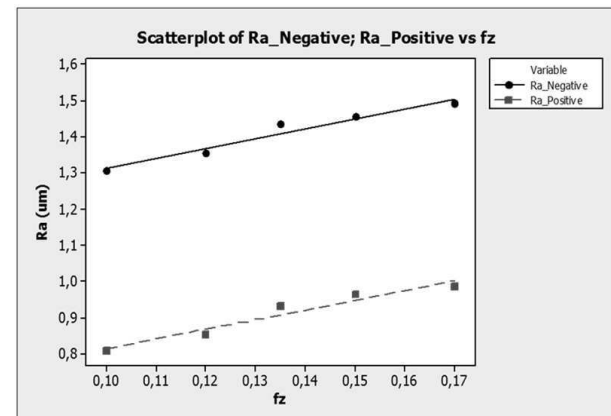


Fig. 9 Surface roughness correlations for steep surfaces

In case of steep surfaces should be considered regression equations as follows:

$$Ra_{negative\ geometry} = 1.035 + 2.776 \times f_z [\mu m] \quad (3)$$

$$Ra_{positive\ geometry} = 0.5438 + 2.698 \times f_z [\mu m] \quad (4)$$

Criterion of the test for case of homoscedasticity:

$$RSC\ negative = 119.80E-5$$

$$RSC\ positive = 132.91E-5$$

$$RSC\ positive + negative = 63176.13E-5$$

$$F_{chtest} = 169.65$$

$$F_{0.95} (m=2, n-2*m=6) = 5.14$$

It is possible find that $F_{0.95} = 5.14 < F_{\text{ctest}} = 169.65$ and then it is possible to reject zero hypothesis that regression equations (3) and (4) are equal and differences R_a on steep surfaces area are randomize only. Practically is possible to say that there is statistically significant difference between tools with positive and negative geometry for machining shallow surface.

4 Conclusion

The article describes data evaluation for case of machining steep and shallow surfaces, using linear regression models, their evidence and dendrograms. We managed to demonstrate that the data characterizing R_a parameter in case of shallow surfaces are statistically significantly different for positive and negative tool geometry which, for example, by a dendrogram or relevant T-test could not be confirmed. The linear regression models were tested using regression triplets followed by Chow's method and shown at 95% confidence level that the tool geometry is statistically significant to the determination of R_a for shallow surfaces.

In the case of steep surfaces dendrogram evaluation clearly demonstrated the dissimilarity in terms of R_a for different cutting conditions and a similar result are obtained even when applying regression triplet and Chow's method.

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