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Prediction and modeling of roughness in ball end milling with tool-surface inclination

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Abstract. The quality of mill finishing of shaped surfaces is influenced by a number of input parameters. Current automated manufacturing systems allow adaptation of the machining process aiming at the final surface quality. Despite all the advantages, these systems require a behavioural model, a prediction of the output, based on the input parameters. Some of these models are summarized in this paper, including contemporary evaluated models as well as their functional dependencies; moreover, offers an application of mill finishing with a ball-end cutter incorporating tool axis or surface inclination.

1. Introduction

Milling is a conventional technology in which the material is removed from the workpiece in the form of chips with a multi-blade cutting tool. The main rotary movement is performed by the tool and the chips are periodically generated according to the number of tool blades. The resulting surface quality of the machined surface consists of a series of elementary surfaces formed by individual cutting edge as well as by entire cutting process. Surface topography is the result of the material removal process due to the relative movement of the tool and the workpiece. In the primary view, it is possible to find a direct correlation of the resulting surface quality with the geometric characteristics of the milling tool.

Predicting surface quality after milling is a challenge at many levels. This is because the surface quality and the associated evaluation parameters are influenced by a number of input factors whose behavior is often non-linear, moreover some of the factors interact with each other. In addition to the primary concern, surface quality is important to the performance of a part and affects, inter alia, durability, friction properties, corrosion resistance and lubricant distribution, heat transfer, light reflectance and fatigue strength, and last but not least the appearance and cost of the part [1-6].

Surface quality is a widespread product quality evaluation parameter and is one of the technological requirements. The following article discusses the surface quality after milling, which is used in multi-axis finish milling. A spherical milling tool is used when milling contoured surfaces with a slope. This avoids the known phenomenon where, in the vicinity of the tool axis, the resulting cutting speed approximate to zero and at this point the material is not being cut.

In the industry, especially in the manufacture of forming tools, mold cavities for foundry and injection molds in particular, surface quality is characterized as the arithmetical mean roughness *Ra*. The *Ra* parameter is widely used in manufacturing practice, although it provides limited information on the condition and quality of the machined surface. This parameter is most often accompanied by the measurement of the parameter *Rz*, however dependent on *Ra*.

2. Prediction models and optimization techniques

Despite the fact that the machining process is influenced by a number of factors related to the machine-tool-workpiece-fixture relationship [7-9], current process machining models are able to suggest the setting of inputs, most often cutting conditions, according to the required surface quality [10]. The methodology of surface quality prediction includes various solution approaches; from simpler ones such as the determination of the kinematic model of surface creation, experimental investigation and surface analysis, the implementation of artificial intelligence (AI) as well as approaches using the design of experiment. Despite a number of methods and models, the researches almost without exception describe surface quality only for a specific case with given boundary conditions. In the absence of a universal surface quality model, re-determination of the input change model is required. A disadvantage of many surface quality models is also the fact that the cutting conditions proposed can be given outside the machine's working range or require precise adjustment sensitivity. Recent studies have focused on investigating the cutting process of the end mill with spherical tool end, known also as a ball end mill cutter, for finishing oblique and contour shaped surfaces [11-12]. Yet few researchers are involved in this issue and there are not enough surface quality models suitable for application in manufacturing practice.

Several important studies are devoted to the relationship between surface quality and the machining process. The authors Benardos and Vosniakos [13] not only determined graphically the factors influencing the cutting process, their great contribution in the area of prediction is the summary and classification of solution approaches. Another general solution is proposed by Lu [14] in the study of the prediction of surface roughness using the artificial intelligence with the contribution of vibration. Quintana [15-19] also continually addresses the relationship between ball milling, surface quality and process stability. Based on previous research in this area, it is possible to categorize the surface quality prediction into the following groups:

a) Kinematic models (based on machining theory)
b) Empirical modeling (experimental analysis of effects, regression analysis)
c) Planned experiment methods (DOE)
d) Artificial intelligence methods (ANFIS, ANN)
e) Advanced methods (GA, Fuzzy, Neuro-Fuzzy, Hybrid methods)

Sadilek and Cep [19] present one of the mechanical *Ra* model (1) for planar surfaces. They emphasize the need to mill off-axis due to zero cutting speed near the tool axis. Therefore, they recommend tilting the tool or workpiece surface and using multi-axis machining operations. Further mechanical model (2) gives Peterka [20], where substitution is performed for inclined tool-workpiece machining, allowing the calculation of theoretical *Ra* values. The model is verified experimentally for various machining methods.

$$Ra = \frac{R^2}{a_e} \times \left\{ \begin{array}{l} arc2\left[\arccos\left(\frac{1}{2}\cos\arcsin\frac{a_e}{2R} + \frac{R}{a_e} arc\arcsin\frac{a_e}{2R} \right) \right] - \\ -\sin 2\left[\arccos\left(\frac{1}{2}\cos\arcsin\frac{a_e}{2R} + \frac{R}{a_e} arc\arcsin\frac{a_e}{2R} \right) \right] \end{array} \right\} \times 1000 \tag{1}$$

$$Ra = \frac{R^2\cos\alpha}{a_e} \left\{ \begin{array}{l} arc2\left[\cos^{-1}\left(\frac{1}{2}\cos\sin^{-1}\frac{a_e}{2R\cos\alpha} + \frac{R\cos\alpha}{a_e} \arcsin^{-1}\frac{a_e}{2R\cos\alpha} \right) \right] - \\ -\sin 2\left[\cos^{-1}\left(\frac{1}{2}\cos\sin^{-1}\frac{a_e}{2R\cos\alpha} + \frac{R\cos\alpha}{a_e} \arcsin^{-1}\frac{a_e}{2R\cos\alpha} \right) \right] \end{array} \right\} \times 1000 \tag{2}$$

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An important author in this area is Quintana, who presents mechanical *Ra* models for planar and inclined surfaces. The results show a relatively good agreement of the theoretical *Ra* with the measurement, but the theoretical calculation of the height inequality in an independent equation, in some cases, varies by up to 75 %. The author explains this mismatch by the thermal contribution and the dynamic effect of the milling process.

Quintana suggests monitoring the process using cause-effect methods using ANN, GA, Fuzzy, or expert systems. The artificial neural networks are used in the later study [15], and focuses on *Ra* modeling for planar surfaces. These relationships and equation (3)

$$Ra = \frac{2}{a_e}\left(R^2\cos^{-1}\left(\frac{\sqrt{R^2-\frac{a_e^{\,2}}{4}}}{2R}\right)+\frac{R}{a_e}\sin^{-1}\left(\frac{a_e}{2R}\right)\right)-\left(\frac{R^2}{a_e}\sin^{-1}\left(\frac{a_e}{2R}\right)+\frac{\sqrt{R^2-\frac{a_e^{\,2}}{4}}}{2}\right)\times$$
$$\times\left[\frac{2R^3}{a_e}\sin^{-1}\left(\frac{a_e}{2R}\right)+2R^2-R\sqrt{R^2-\frac{a_e^{\,2}}{4}}-\left(\frac{R^2}{a_e}\sin^{-1}\left(\frac{a_e}{2R}\right)+R-\frac{\sqrt{R^2-\frac{a_e^{\,2}}{4}}}{2}\right)^2\right]^{1/2} \tag{3}$$

are inputs for ANN system using a dual-layer feed-forward network, a Levenberg-Marquardt learning algorithm and one hidden layer of 20 neurons. The entire model includes, among other inputs, vibration, the effect of cooling, and in total Quintana conducted 250 experiments. The obtained excellent degree of accuracy between the model and the measured data shows that ANN is the right way for modeling the machining process.

Suresh [21] offers two mathematical models of *Ra*, which were compiled from measured data and evaluated by RSM. However, the first order model in this paper offers limited descriptiveness, and therefore a second order polynomial model (4) with a regression coefficient $R^2 = 0.9305$ is established. The equation is valid for milling planar surfaces with side radius cutters. The author used genetic algorithms with a population size of 20 and a maximum number of 500 generations to find the optimal cutting geometry of the tool and cutting conditions for the best surface quality.

$$Ra = 0.20924-0.0574(\ln v_c+0.793536)^2+0.0215(\ln v_f+3.5907)^2+$$
$$+0.3506(\ln\gamma+0.4066)^2+0.2746(\ln r_\varepsilon+0.394756)^2 \tag{4}$$

The Jatti [22] model (5) uses RSM with the Box Behnken method with three-level factorial design and other centered, which is a 2nd order polynomic function and serves as input for GA optimization.

$$Ra = 9.01938+0.00194971n-0.0101682v_f-6.41036a_p-2.54626\times10^{-7}n^2+$$
$$+4.08583\times10^{-6}v_f^{\,2}+5.92333a_p^{\,2}-3.42857\times10^{-7}n\times v_f-$$
$$-4.31429\times10^{-4}n\times a_p-2\times10^{-4}v_f\times a_p \tag{5}$$

The model works with an average error of 5.9 %, a maximum error of 12.84 % for machining Al-Si12 alloys, used for specific application in foundry purpose.

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Explanation of parameters and abbreviations in equations (1-5) and chapter above is given as:

R	cutting tool radius (mm)
v_c	cutting speed (m/min)
n	revolutions per minute (min^{-1})
v_f	feed rate (mm/min)
f_z	feed per tooth (mm)
a_p	axial depth of cut (mm)
a_e	radial depth of cut (mm)
r_ε	mill cutter radius (mm)
α	surface / tool inclination angle (°)
γ	tool rake angle (°)
RSM	Response surface methodology
GA	Genetic algorithm
ANN	Artificial neural networks
DOE	Design of experiments

3. Influence of inclination angle

Shape surfaces on parts can be classified into two categories for the purpose of this study. Shallow surfaces are characterized by the inclination angle α relative to the horizontal surface (0 ° - 30 °>, the steep surfaces then within the inclination angle α (30 ° - 90 °).

It can be seen from the evaluation and in the figure 1 that, when milling a surface with a slight slope, referred to as shallow, the better surface quality is achieved under the same technological conditions than in the case of surfaces with a greater steepness. The trend of the dependence on the angle of inclination is exponential with slight gradient. The behavior is corresponding to the variating cutting forces as the angle of inclination changes, the low stiffness of the tool in the lateral directions, vibrations and other dynamic machining phenomena.

The radial depth of cut a_e is identified by literature and analytical analysis as the most significant influencing parameter on surface quality when milling with a ball end mill tool. If the parameter a_e is rising, which means that the spacing between parallel cuts increases, this obviously leads to a deterioration of the surface quality.

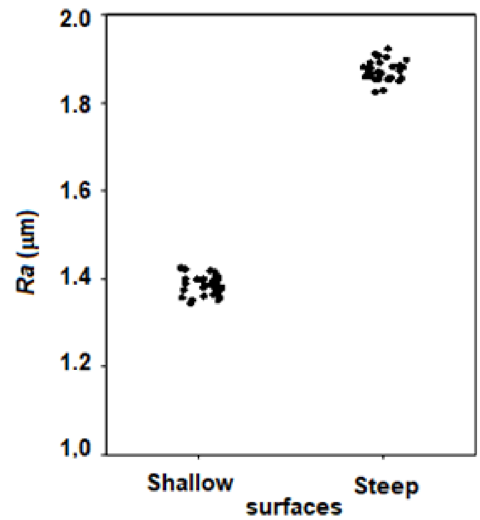

Figure 1. Individual *Ra* sets of milling surfaces with shallow and steep inclination angle ($\alpha_{shallow}$ = 15 %, α_{steep} = 75 %, a_e = 0.6 mm, f_z = 0.1 mm).

As can be seen in the figure 2, the course of the roughness parameter *Ra* is exponential, and mathematical interpretation can evaluate recursively values that cannot be measured, moreover predict the *Ra* roughness for specific machining conditions. A frequent limiting criterion is the time the tool is engaged into the cut. The parameter is directly related to tool life and tool wear; at the same time, it is associated with the cost of operating the machine for machining large-dimension parts and allows the selection of process parameters with respect to time constraints.

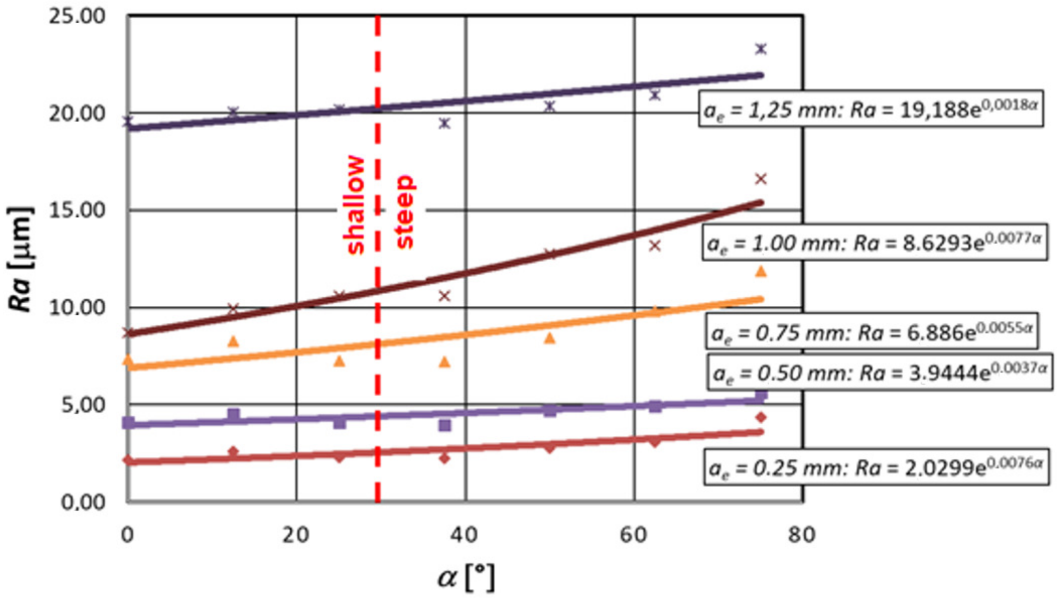

Figure 2. Dependence of *Ra* on the inclination angle α and the radial depth of cut a_e (AW 7022, D = 5 mm).

4. DOE and significant parameters

In general, design of experiments (DOE) is used to obtain process information based on a methodological plan. Not all possible combinations of options need to be measured to determine process parameters, saving time and resources. On the other hand, it requires precious accuracy when determining output parameters with minimal variance.

With respect to the mentioned facts, the data were evaluated during milling of inclined surfaces. DOE allows to analyze multiple input parameters in one cycle. Based on the experiments and their values transformed into the signal-to-noise ratio, the main effects (table 1) and their order of significance by factors were determined.

Table 1. Order of effects by factor.

Level	1	2	3	4	5
***F*1**	α	D	l	a	v_f
***F*2**	a	D	l	v_f	α
***F*3**	D	a	v_f	l	α
Ra	a	v_f	l	D	α
Rz	a	v_f	l	D	α
Rmr	D	a	v_f	α	l

*F*1	passive force (N)
*F*2	feed force (N)
*F*3	main cutting force (N)
Ra	arithmetical mean roughness value (µm)
Rz	mean roughness depth (µm)
Rmr	material component of the profile (µm)
α	surface / tool inclination angle (°)
D	cutting tool diameter (mm)
a	radial depth of cut (% × ∅D)
l	cutting tool ejection in the clamping system (mm)
v_f	feed rate (mm/min)

According to the first two levels, the cutting force components are influenced primarily by the tool selection and its diameter *D*, the radial depth of cut *a* and the angle of inclination α in one case. The main cutting force *F*3 is the largest component to the total force resultant and its size is influenced by the tool diameter *D*, while the smallest contribution has the inclination angle α, which for the finish milling relates to the small size chip cross-section. The feed force *F*2 is influenced mainly by the radial depth of cut *a,* and similarly to the *F*3 inclination angle does not play significant role. On the other hand, the magnitude of the passive force component *F*1 is affected by the tool geometry and inclination angle α, however the smallest influence has the feed rate.

The roughness height parameters *Ra*, *Rz* are interdependent parameters that are determined from the same roughness profile. Therefore, they have the same order of significance as can be seen in the table 1. The material proportion *Rmr* is significantly influenced by the tool (mill cutter diameter *D*) and radial depth of cut *a*. These are primarily variables that affect the frequency characteristics of the roughness profile and can be said to have particular influence on the regularity of movement during machining and creation of the new surface. The experiment revealed that the extrusion of the tool and the associated stiffness of the tool have no significant effect on the material component of the profile.

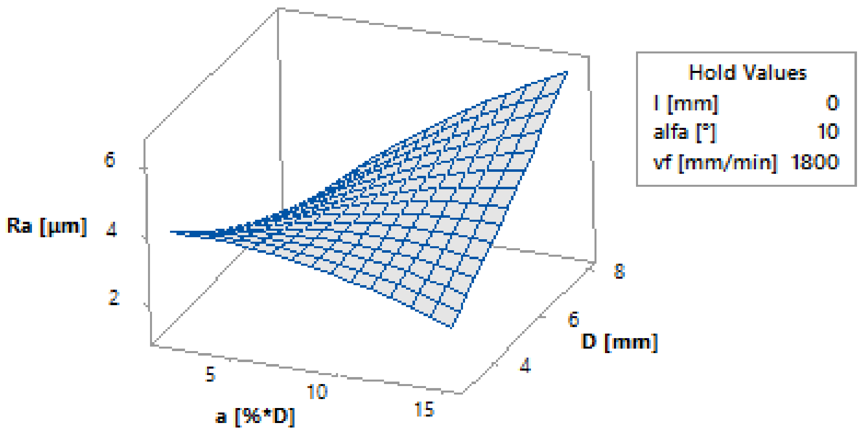

Figure 3. Surface plot of *Ra* for radial depth of cut *a* and tool diameter *D*.

The most ruling milling parameters for optimum surface quality are radial depth of cut *a*, and tool geometry, characterized by the diameter *D* of the mill cutter. In the plot of figure 3, a deterioration of the surface quality with increasing parameters *a* and *D* can be observed. However, it is necessary to note instability at smaller radial depths and the for small tool diameters, where surface quality is influenced by other associated process phenomena, resulting in an improvement in the observed parameter *Ra*. The overall behavioral model obtained by the DOE has a mathematical interpretation in the following equation (6):

$$\begin{gathered} Ra = -132.3 + 1.186 \times l - 0.2673 \times a - 1.12 \times D + 0.2034 \times \alpha + \\ + 0.1537 \times v_f - 0.02027 \times l \times l - 0.009731 \times a \times a + 0.031 \times D \times D - \\ - 0.007986 \times \alpha \times \alpha - 0.00043 \times v_f \times v_f + 0.008198 \times l \times a - \\ - 0.02412 \times l \times D + 0.000322 \times l \times \alpha - 0.000455 \times l \times v_f + \\ + 0.1055 \times a \times D \end{gathered} \tag{6}$$

The obtained equation shows the dependence of the parameter *Ra* on the cutting conditions (*a*, v_f), the tool geometry (*D*) but also on the length of the tool ejection *l* above the recommended settings.

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5. Conclusion

Only a small percentage of research is contributed to modeling, predicting, and optimizing the surface quality of inclined and shaped surfaces after machining. On the basis of the research analysis it can be observed that the surface quality prediction of many theoretical models include a significant error between the measured and predicted values or the application is possible only in a limited range of materials, tools and cutting conditions. Despite this fact, we can observe the increasing demand for the new methods of processing engineering data using advanced statistics, design of experiments and artificial intelligence.

Machining technology by milling does not lose its importance even as finishing operation. The mill finishing may achieve comparable close surface quality to grinding with commercially available tools and machine options. The aim is to minimize or prevent subsequent finishing of the surfaces by grinding, which arise undesirable temperature field and stress states into the surface layer.

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