Int j simul model 21 (2022) 3, 417-428
Original scientific paper

OPTIMIZATION OF SURFACE ROUGHNESS BASED ON TURNING PARAMETERS AND INSERT GEOMETRY

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Abstract
This study is focused on dry longitudinal turning of AISI steel using CVD coated cutting inserts. The machining was conducted at different levels of cutting speed, feed, depth of cut, corner radius, rake, inclination and approach angles. Surface roughness was measured after each experiment, and statistical analysis was used to derive an empirical, regression model for arithmetical mean surface roughness. The regression model was used to theoretically minimize surface roughness, followed by additional verification experiments. The 95 % confidence interval constructed using ten additional batteries of experiments, contained the theoretically predicted minimum roughness of $Ra = 0.238$ μm. The mean absolute prediction error of the optimal roughness equals 0.006 μm. The results reveal practical applicability of the developed model.
(Received in March 2022, accepted in July 2022. This paper was with the authors 1 week for 1 revision.)

Key Words: Surface Roughness, Turning Parameters, Insert Geometry, Modelling, Optimization

1. INTRODUCTION

To obtain workpieces with the required configuration and characteristics, a number of various machining operations must be used. Machining is a complex physico-chemical process which has to meet various requirements such as quality, reliability, productivity, profitability, flexibility, etc., whereby numerous controlled and uncontrolled factors influence the effectiveness of the output parameters of machining [1-3].

Turning is one of the most important and most widely used machining operations in industry. It can be performed on various machine tools, using different types of cutting tools and fixtures. Workpieces can undergo rough and finishing turning. There is a large number of workpiece geometries which can be turned to finishing dimensions. The goal of the finishing turning is to avoid or diminish additional machining, which allows cost reductions and time efficiency. The resulting surface roughness is not only one of the most relevant parameters regarding the quality assessment, but also influences performance of machined parts, which makes it one of the quality indicators that buyers most often specify. Good surface quality is equally important as the dimensional accuracy, geometric tolerances, and product specification. Surface roughness mostly depends on workpiece material properties, cutting tool properties, fixture characteristics, machining parameters and machining conditions. Roughness forming mechanism also depends on numerous factors which are difficult to control, which prohibits development of an all-round solution to this problem. Due to their stochastic nature, it is practically impossible to encompass all input variables. It is always possible to take partial approach to solving this problem, but advantage should be given to a comprehensive solution. Turning is used to machine workpieces of various materials, among which steels are prevalent. AISI 1045 is one of the frequently used steels. It features good machinability and high strength.

Its typical applications include gears, die forging, hot upsetting, shafts, axles, bolts, studs, pinions, casters, support plates, etc.

Many researchers have analysed surface roughness produced during turning of AISI 1045 steel. For instance, Noordin et al. [4] used RMS for surface roughness prediction. Surface roughness increased with increasing feed and with decreasing speed. As side cutting edge angle increased, the roughness first decreased, followed by an increase. Bhattacharya et al. [5] used Taguchi design and ANOVA to determine the contribution of the cutting speed, feed, and depth of cut to surface roughness. The results showed a significant effect of cutting speed on the surface roughness. Hwang and Lee [6] presented an investigation into the MQL (minimum quantity lubrication) and wet turning processes in order to predict surface roughness. The effect of cutting speed and feed rate was dominant, while the effect of depth of cut was relatively small. Cutting speed and feed rate exhibited a nonlinear relationship with surface roughness. Cutting speed and depth of cut showed opposite effects on surface roughness. MQL turning yielded better surface roughness compared with wet turning. Esteves Correia and Paulo Davim [7] compared the influence of inserts geometry on surface roughness. Surface roughness values increased a lot with the feed rate while somewhat decreasing with the cutting speed. At higher feeds, turning with conventional inserts yielded higher values of surface roughness in comparison with wiper inserts. Kohli et al. [8] developed a fuzzy model to predict surface roughness. Surface roughness improved with decreasing feed, decreasing depth of cut and increasing cutting speed. Using Taguchi method, Senthilkumar and Tamizharasan [9] analysed the effects of geometrical parameters of cutting insert (cutting insert shape, corner radius, relief angle) on surface roughness. They reported high level of interaction between the geometrical parameters of a particular cutting tool insert, noting a pronounced interaction effect between cutting insert shape and corner radius. ANOVA showed that cutting insert shape was the most significant parameter, followed by corner radius, while the effect of relief angle was negligible. Senthilkumar et al. [10] investigated the influence of the machining parameters and approach angle on surface roughness. They coupled grey relational analysis and fuzzy logic technique for the purpose of evaluation. They found that surface roughness improved with decreasing feed, depth of cut, and approach angle. The increase of cutting speed improved surface roughness to a point, after which it started to deteriorate. Xiao et al. [11] studied the effect of spindle speed, feed and depth of cut towards surface roughness. According to their results, surface roughness increased with increasing feed. The increase of spindle speed resulted in initial increase of surface roughness, followed by its decrease, while the increase of the depth of cut resulted in initial decrease of surface roughness, followed by its increase. Analysis of variance suggested that feed had great effect on surface roughness. Abbas et al. [12] evaluated the effect of cutting speed, depth of cut, feed and corner radius on surface roughness using Taguchi method, ANOVA and RSM. They noted that the increase of feed and depth of cut diminished the surface quality, while higher cutting speed and corner radius contributed to its improvement. Kimakh et al. [13] analysed the effect of the cutting speed, feed and the corner radius on the surface roughness, finding that surface roughness improves with the increase of cutting speed, while being negatively impacted by feed rate. Although corner radius had little influence on surface roughness, it strongly affected the influence of feed and cutting speed on the surface roughness. Masoudi et al. [14] investigated the effects of nozzle position, workpiece hardness, and tool type on the surface quality. The results demonstrated that lubrication systems have a significant impact on the surface topography. The MQL system strongly reduced the roughness compared to the dry and wet machining. Montilla-Montaña et al. [15] compared the machinability under conventional machining and pulsed-current-assisted machining. Surface roughness was lowest for the smallest displacement, high velocity and low rake angle, while using electro pulses. Raja et al. [16] analysed the effect of untreated and deep cryogenically treated tools on surface roughness, using the fuzzy inference logic and the Taguchi method.

The results showed that surface roughness decreased at a higher level of speed and depth of cut, as well as a lower level of feed. Camposeco-Negrete and Calderón-Nájera [17] optimized a turning process using the response surface methodology and the desirability analysis. Surface roughness was lower for the reduced feed, cutting speed and depth of cut. Abbas et al. [18, 19] optimized machining parameters and cooling conditions (dry, wet, MQL) for minimum surface roughness. They reported that surface roughness improved with reduced feed, depth of cut, and cutting speed, with the application of MQL cooling strategy. Jiang et al. [20] presented a method to optimize cutting parameters, considering the trade-off among carbon emissions, surface roughness, and processing time. The amount of carbon emissions and surface roughness were found to be inversely proportional. The same relationship was also seen between the surface roughness and the processing time. Equeter et al. [21] presented the results of an exploratory study on the influence of tool flank wear on surface roughness. Significant correlation was found between surface roughness and cutting tool flank wear. Abidi [22] performed Taguchi method and ANOVA analysis to determine the influence of turning parameters on surface roughness. The results showed that increased feed results in increased surface roughness, while increasing the cutting speed slightly improves the surface quality. Paese et al. [23] performed an experimental investigation based on ANOVA and RSM techniques to determine how the factors such as cutting speed, feed, depth of cut, corner radius, substrate and coating method influence surface quality. The PVD-coated inserts in combination with lower feed and higher corner radius generated the lowest surface roughness. Vijaya Ganesa Velan et al. [24] studied the effect of turning parameters and high-pressure coolant on surface roughness. The results showed lower surface roughness when the cutting speed is increased, whereas higher feeds resulted in increased surface roughness. Application of coolant at a higher pressure substantially reduces surface roughness. Abdulateef and Taha [25] reported utilization of computer vision and backlight techniques to determine the surface roughness of a workpiece under a variety of process parameters. The comparison revealed that the vision method provided precise and consistent results in comparison with the traditional stylus method. Szczotkarz et al. [26] compared three types of coatings deposited with the PVD method on a sintered carbide insert (TiN, TiAlN and TiC). They showed that for the TiAlN coated insert, lower surface roughness was observed at lower cutting speeds and higher feeds, while for the TiC coated insert, higher cutting speeds lead to lower surface roughness. Vukelic et al. [27] modelled turning process with a constant cutting force using ANN. They reported that the surface roughness first improves and then worsens with the increase in cutting force, cutting time and number of revolutions. Su et al. [28] developed prediction models for surface roughness considering tool wear evolution. They used cutting depth, feed, spindle speed, and tool flank wear as input variables, while orthogonal experimental results were employed as training points to establish the prediction models based on support vector regression algorithm. Their results showed that the models based on cutting parameters and tool wear have higher prediction accuracy than the prediction models solely based on the cutting parameters.

This review shows that various methods and techniques have been employed for the investigation of surface roughness problem. As the basis of scientific research, experimental approach is increasingly being augmented by modelling and optimization. Design of experiment, ANOVA, RMS, Taguchi, SVR, and artificial intelligence are widely used to reduce costs and time of experimental research while allowing accurate prediction of surface roughness. In addition, development of predictive models for surface roughness represents the basis of optimization based on various criteria. For the turning process specifically methods and techniques of AI are most frequently used. These methodologies have their comparative advantages and disadvantages. On the other side, most of them suffer from limitations and idealizations which contribute to errors, which emphasizes the importance of experimental verification of the obtained results.

Analysis of previous investigations indicates that there are numerous complex, interacting factors which impact the final surface quality obtained by turning. It is possible to identify certain factors which are generally most vital to reducing surface roughness. A combination of small feed [29] and corner radius [30], and efficient cooling and lubrication [31], generally leads to good surface quality. Moreover, the use of wiper turning inserts instead of their conventional counterparts, also yields good finished surface [32]. Vibration minimization will also improve surface roughness [33]. In spite of the previous investigations, phenomena which are responsible for the formation of surface roughness are still insufficiently understood due to their highly complex and interrelated nature, while the remaining factors can affect surface quality both ways, thus still holding us away from an all-round solution of the problem. Integration of a larger number of input factors into the models has the potential to increase their accuracy, especially in the case of finishing turning, where the influence of the sum of variables is especially crucial.

The goal of this investigation is to generate a model for prediction and optimization of surface roughness which would be applicable on a wider scale, while reducing the costs of experimentation. Development of a sufficiently accurate empirical model shall be an important step towards efficient production planning, selection of processing regime parameters and cutting tools. Furthermore, in a real industrial application, such empirical model shall minimize errors, i.e. defect and reworking, while avoiding unnecessary costs due to producing surface quality above the required level. For the purpose of investigation, modelling, and optimization of finishing turning of AISI 1045 steel, the authors considered a comprehensive set of input factors, including not only the machining parameters, but also the cutting tool geometry. A total of seven independent variables were selected for this study, of which three pertain to machining (cutting speed, feed, depth of cut), while the remaining four describe cutting tool geometry (corner radius, rake angle, inclination angle, approach angle). The results obtained based on a statistically organized experiment, shall be used to construct empirical model which best allows process modelling, with the goal to minimize surface roughness as the result of finishing turning.

2. MATERIALS AND METHODS

Research methodology is schematically shown in Fig. 1.

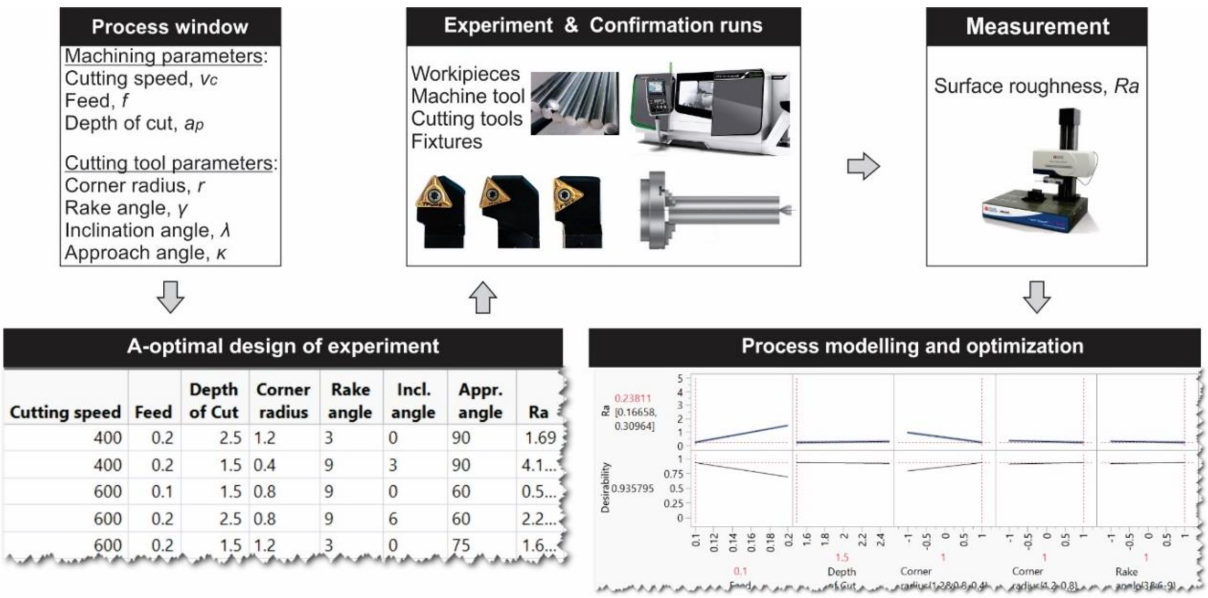

Figure 1: Research methodology.

Experiments were conducted with workpieces dimensioned Ø 40 × 400 mm, made of AISI 1045 steel. Chemical composition of AISI 1045 steel is outlined in Table I, while mechanical and physical properties are tabulated in Table II.

Finishing longitudinal turning was performed on a CNC lathe (Dmg Mori Seiki CTX 510 Ecoline), which features cost-efficient power consumption, excellent rigidity and vibration absorption, high accuracy and precision. Vital technical data of this CNC lathe are: main spindle power 33 kW, maximum torque 630 Nm, maximum speed range 3250 rpm, maximum tailstock force 1250 daN, maximum turning diameter Ø 465 mm and maximum turning length 1050 mm.

Table I: Chemical composition of AISI 1045 carbon steel.

Element	**Content** (%)
Carbon, C	0.43-0.50
Manganese, Mn	0.60-0.90
Sulfur, S	0.05 (max)
Phosphorous, P	0.04 (max)
Iron, Fe	Balance

Table II: Mechanical and physical properties of AISI 1045 carbon steel.

Properties	**Value**
Tensile strength	585 MPa
Yield strength	450 MPa
Modulus of elasticity	200 GPa
Poisson’s ratio	0.29
Brinell hardness	163
Density	7.87 g/cm^3

Workpiece locating and clamping was performed using three-jaw chuck (main spindle) and rotary centre (tailstock). This combination of fixtures allowed sufficient stiffness and minimal compliance of the fixture-workpiece assembly.

Seven parameters were varied, three numerical-kinematic factors, i.e., cutting speed, feed, depth of cut, and four categorical-geometrical factors (corner radius, rake, inclination, and approach angle). Continuous parameters were varied on two levels, while the categorical ones were varied at three levels. The design of experiment was based on A-optimal design which allowed us to minimize the number of required runs while being able to efficiently and reliably identify active subset of the factors. Besides minimizing the average variance of the parameter estimates, an A-optimal design significantly reduces the worst prediction variance compared with D-optimal designs, as discussed by Jones et al. [34]. Each of the 27 unique experiments from the design table was performed using a brand new, CVD-coated cutting insert. The common characteristics of the cutting inserts used in this experiment are: insert shape code T, cutting edge count 3, insert included angle 60°, clearance angle 7°, insert thickness 4 mm, fixing hole diameter 4.5 mm, inscribed circle diameter 9.53 mm, theoretical cutting edge length 16.5 mm, and cutting edge effective length 14.5 mm. Machining parameters and cutting tools were selected according to recommendations of cutting inserts manufacturer, and were based on workpiece material, workpiece geometry, equipment characteristics, stability, etc.

The output variable in this experiment, arithmetical mean surface roughness, was measured and recorded for all 27 experiments. Surface roughness measurements were performed on a Talysurf measuring device with the following basic characteristics: radius accuracy 0.006 %, roughness noise less than 10 nm *Rz*, and gauge resolution down to 0.3 nm. The column and the base of the measuring device are made of composite granite to provide high vibration dampening, thermal inertia and stiffness throughout the measuring cycle. In addition, the measuring instrument has passive air mounts in the anti-vibration system function. *Ra* values were evaluated within the evaluation length, which consisted of five sampling lengths, i.e., the five cut-off wavelengths of the profile filter. Gaussian filters were used to separate roughness and waviness characteristics. The measurement was conducted with the cut-off length of 0.8 mm, sampling length of 0.8 mm, and evaluation length of 4 mm. Measurements were taken along the contour lines on the workpiece, in ten radial directions oriented at 36° relative to the axis of the workpiece. Surface roughness values were calculated as mean values derived from the ten repeated measurements.

Shown in Table III are the factors in this design of experiment, with their corresponding levels. While the continuous factors are varied at their high and low levels, the categorical factors are varied at three levels which correspond to real values of parameters in the commercially available cutting tool inserts.

Table III: Process window.

Parameter	**Low level**	**Middle level**	**High level**
Cutting speed, v_c (mm/min)	400	/	600
Feed, f (mm/rev)	0.1	/	0.2
Depth of cut, a_p (mm)	1.5	/	2.5
Corner radius, r (mm)	0.4	0.8	1.2
Rake angle, γ (°)	3	6	9
Inclination angle, λ (°)	0	3	6
Approach angle, κ (°)	60	75	90

3. RESULTS

Based on the table of experiment generated for the A-optimal design with 27 runs, all experiments were performed using the levels defined in Table III. The results of measurements are reported in Table IV.

Table IV: The results of measurements.

Run	v_c (mm/min)	f (mm/rev)	a_p (mm)	r (mm)	γ (°)	λ (°)	κ (°)	Ra_1 (μm)	Ra_2 (μm)	Ra_3 (μm)	Ra_4 (μm)	Ra_5 (μm)	Ra_6 (μm)	Ra_7 (μm)	Ra_8 (μm)	Ra_9 (μm)	Ra_{10} (μm)
1	400	0.2	2.5	1.2	3	0	90	1.69	1.72	1.69	1.67	1.68	1.73	1.68	1.68	1.67	1.69
2	400	0.2	1.5	0.4	9	3	90	4.20	4.22	4.10	4.12	4.16	4.23	4.13	4.15	4.12	4.10
3	600	0.1	1.5	0.8	9	0	60	0.52	0.51	0.50	0.50	0.52	0.50	0.51	0.52	0.50	0.51
4	600	0.2	2.5	0.8	9	6	60	2.25	2.27	2.19	2.21	2.23	2.25	2.22	2.24	2.21	2.19
5	600	0.2	1.5	1.2	3	0	75	1.61	1.66	1.60	1.63	1.65	1.64	1.62	1.66	1.60	1.61
6	400	0.2	1.5	0.8	6	3	90	2.38	2.43	2.33	2.36	2.40	2.41	2.36	2.41	2.33	2.38
7	600	0.2	1.5	0.4	3	0	75	4.81	4.96	4.89	4.85	4.94	4.97	4.85	4.93	4.89	4.81
8	600	0.1	2.5	1.2	6	6	75	0.42	0.43	0.41	0.42	0.42	0.42	0.41	0.43	0.43	0.41
9	400	0.1	2.5	0.4	3	3	60	1.32	1.35	1.29	1.31	1.33	1.34	1.33	1.33	1.35	1.29
10	400	0.1	1.5	0.8	3	6	90	0.67	0.67	0.65	0.65	0.66	0.67	0.65	0.64	0.66	0.65
11	400	0.2	2.5	0.4	6	0	60	4.95	4.97	4.83	4.85	4.90	4.98	4.86	4.89	4.90	4.85
12	400	0.1	1.5	1.2	9	0	60	0.35	0.36	0.34	0.35	0.35	0.36	0.34	0.35	0.35	0.35
13	400	0.2	1.5	0.4	9	6	75	4.45	4.50	4.32	4.37	4.41	4.49	4.37	4.43	4.41	4.37
14	600	0.1	1.5	0.4	6	0	90	1.01	1.03	0.99	1.00	1.02	1.03	1.01	1.03	1.02	1.00
15	600	0.2	1.5	1.2	6	3	60	1.55	1.61	1.58	1.56	1.60	1.61	1.57	1.61	1.60	1.56
16	600	0.2	2.5	0.8	6	0	90	2.32	2.37	2.27	2.30	2.34	2.37	2.30	2.33	2.34	2.30
17	400	0.2	1.5	1.2	3	6	60	1.77	1.83	1.75	1.79	1.81	1.83	1.79	1.81	1.79	1.75
18	600	0.1	1.5	0.8	3	3	75	0.61	0.63	0.61	0.62	0.63	0.62	0.62	0.61	0.62	0.61
19	600	0.2	2.5	1.2	9	6	90	1.42	1.48	1.45	1.44	1.46	1.47	1.44	1.41	1.44	1.45
20	600	0.1	1.5	0.4	6	6	60	1.24	1.30	1.27	1.26	1.28	1.29	1.27	1.27	1.24	1.26
21	400	0.2	1.5	0.8	6	6	75	2.51	2.55	2.45	2.47	2.53	2.55	2.46	2.51	2.51	2.47
22	400	0.1	2.5	0.8	9	0	75	0.54	0.53	0.52	0.54	0.52	0.53	0.54	0.51	0.53	0.54
23	600	0.2	2.5	0.8	3	3	60	2.55	2.63	2.53	2.58	2.61	2.63	2.56	2.61	2.63	2.55
24	400	0.1	2.5	1.2	6	3	75	0.40	0.42	0.41	0.41	0.41	0.41	0.40	0.41	0.42	0.41
25	600	0.2	2.5	0.4	9	3	75	4.17	4.13	4.29	4.21	4.25	4.13	4.21	4.22	4.29	4.21
26	600	0.1	2.5	0.4	3	6	90	1.34	1.31	1.28	1.30	1.32	1.33	1.30	1.29	1.28	1.30
27	600	0.1	1.5	1.2	9	3	90	0.35	0.34	0.33	0.34	0.34	0.34	0.33	0.36	0.33	0.34

Statistical analysis was performed in SAS JMP 14. The regression model was selected according to three parameters: Akaike information criterion (*AIC*), Bayesian information criterion (*BIC*) and coefficient of determination (R^2). To facilitate the adoption of the final regression model, two common information criteria were used, *AIC* and *BIC*. Both criteria essentially penalize inadequate fitting, smaller values indicating models with better prediction abilities. The adopted model has 15 terms and meets both criteria in that they reach their minimal values. For more complex models, the *BIC* continues to diminish, while the *AIC* grows. The adopted regression model is linear and explains over 99 percent of process variability. Its root mean square error (*RMSE*) is small compared to mean value of response, thus yielding narrow confidence interval. Summary of fit and analysis of variance are given in Tables V and VI, respectively.

Table V: Summary of fit.

Element	Value
R^2	0.999756
R^2_{adj}	0.999471
RMSE	0.03332
Mean of Response	1.906222
Observations	27

Table VI: Analysis of variance.

Source	*DF*	Sum of squares	Mean square	*F* ratio
Model	14	54.542912	3.89592	3509.075
Error	12	0.013323	0.00111	Prob > *F*
Total	26	54.556235		<.0001*

Shown in Table VII are estimated regression coefficients sorted by ascending order of *p*-values. It is evident that the most influential factor is feed, followed by the corner radius and the remaining factors. Among the interactions, the most impactful to the surface quality is the two-way interaction between feed and corner radius. Although depth of cut is not statistically significant per se, it is a part of the statistically significant interaction with the inclination angle. As can be seen from Table VII, the cutting speed and approach angle do not figure in the adopted model.

Table VII: Estimated regression coefficients (* statistical significance).

Term	Estimate	Std error	*t* ratio	Prob>|*t*|
Intercept	2.0335718	0.009382	216.75	<.0001*
f (0.1, 0.2)	1.1134142	0.00861	129.32	<.0001*
r {1.2&0.8-0.4}	-0.839439	0.00999	-84.03	<.0001*
$f \times$ (r {1.2&0.8-0.4} - 0.33333)	-0.54846	0.009049	-60.61	<.0001*
r {1.2-0.8}	-0.224897	0.008628	-26.07	<.0001*
γ {3&6-9}	0.1447973	0.008194	17.67	<.0001*
$f \times r$ {1.2-0.8}	-0.16767	0.010016	-16.74	<.0001*
(r {1.2&0.8-0.4} - 0.33333) $\times$ (γ {3&6-9} - 0.33333)	-0.11126	0.01283	-8.67	<.0001*
γ {3-6}	0.0574647	0.009028	6.37	<.0001*
λ {6-3&0}	0.0540529	0.009508	5.68	0.0001*
$f \times$ (γ {3&6-9} - 0.33333)	0.0663919	0.013749	4.83	0.0004*
(γ {3&6-9} - 0.33333) $\times$ λ {3-0}	0.0426176	0.011096	3.84	0.0023*
$a_p \times$ (λ {6-3&0} + 0.33333)	-0.029261	0.008876	-3.30	0.0064*
λ {3-0}	0.0291962	0.010412	2.80	0.0159*
a_p (1.5, 2.5)	0.0134771	0.007735	1.74	0.1070

The main effects of the terms which qualified for the adopted regression model, are shown in Fig. 2. The profiler plot shows factor settings which are the result of maximization of desirability function, which, in the case of this study, minimizes mean arithmetical surface roughness. As shown in Fig. 2, the adopted model predicts mean value of $Ra = 0.238$ μm.

The adopted regression model was verified experimentally, through ten additional confirmation experiments. Confirmation experiments were performed with the optimized settings shown in the prediction profiler (Fig. 2). Measured *Ra* values were subsequently used to construct the experimental 95 % confidence intervals which should contain the predicted *Ra* mean.

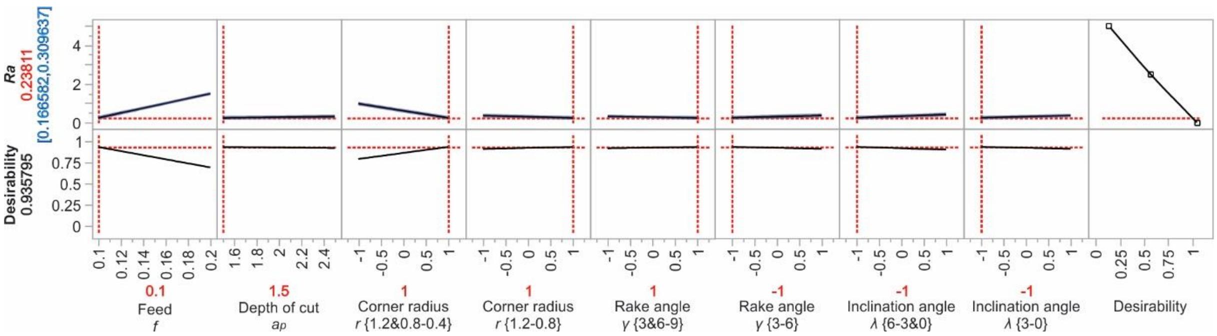

Figure 2: Prediction profiler.

Although the cutting speed and approach angle were left out of the adopted regression model, the diagrams shown in Fig. 3 were consulted to decide on their levels for the purpose of conducting the confirmation experiments. *Ra* residuals were plotted against cutting speed and approach angle, and the resulting dispersions were observed. Considering the low and high levels on both plots, one concludes that keeping the cutting speed at its high level (600 mm/min) contributes to reduction of dispersion, i.e., the dispersion equals 0.064, as opposed to 0.080 at the low level (400 mm/min). Similarly, the approach angle of 90° is favoured due to yielding lowest dispersion compared to the remaining two levels.

With that in mind, confirmation experiments were conducted with the following factor values: cutting speed v_c = 600 mm/min, feed f = 0.1 mm/rev, depth of cut a_p = 1.5 mm, corner radius r = 1.2 mm, rake angle γ = 6°, inclination angle λ= 6° and approach angle κ = 90°.

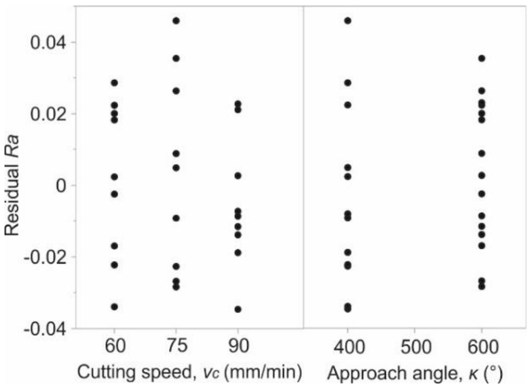

Figure 3: Residuals of surface roughness *Ra* versus cutting speed v_c (mm/min) and approach angle κ (°).

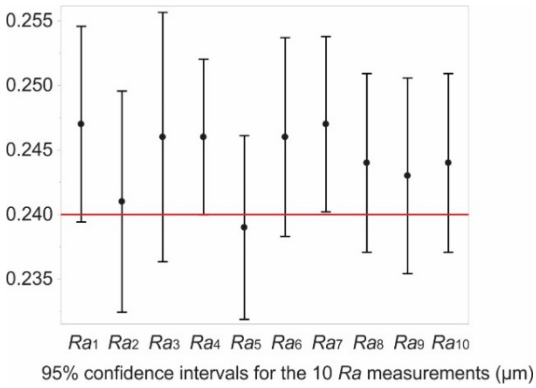

Figure 4: Results of confirmation runs.

Each of the ten confirmation experimental batteries consisted of ten measurements. The measurements were used to generate ten 95 % confidence intervals. The intervals are shown in Fig. 4, where the red reference line marks the mean *Ra* predicted by the regression model. As can be seen, only one of the experimentally constructed *CI*'s does not contain the predicted mean value. Also, the 95 % *CI* = [0.240, 0.248] constructed based on the total of 100 measurements, although very narrow, misses the predicted mean *Ra* by 0.002 μm.

4. DISCUSSION

The quality of machined surface largely depends on the values and relative magnitudes of corner radius and feed. At constant feed, smaller corner radii yielded worse surface quality. This can be attributed to varying rake angle alongside the cutting edge, as well as the uneven distribution of pressure within the cutting zone. As the corner radius increases, the generated heat is dispersed over the larger contact area between the tool tip and workpiece material, thus lowering the thermal load and tool wear. Larger corner radius can also cause an increase in chatter and vibrations, which was not recorded during this study. The use of chip breakers contributed to generation of broken chip during the experiment. In addition, larger radii contribute to a more balanced distribution of generated heat.

Surface roughness increases at higher feeds, i.e., peaks and valleys generated by the tool tip on workpiece surface become ever wider and deeper. Theoretically, geometrical surface roughness is a function of feed for a given corner radius, which explains better surface quality at smaller feeds.

The increase of rake angle contributes to surface quality improvement. Larger rake angle diminishes the cutting tool wedge angle, which results in a sharper tool. Up to a point, this contributes to reduction of surface roughness. However, as the rake angle continues to increase, cutting tool wedge gets weaker, i.e., there is a loss in cutting edge stability, which leads to a mild deterioration of surface quality. Moreover, smaller rake angles can contribute to better chip breaking, due to less cohesion between the neighbouring layers during the chip creation.

The inclination angle directly impacts the direction in which the chip flows during the cutting process. At zero inclination angle, the chip flows orthogonally to the cutting edge direction. As the approach angle increases, the chip flows in the direction opposite to feed, towards the workpiece. During this experiment, a slight damage to machined surface was observed due to chip impact.

The increase of depth of cut contributes to reduced tool life. The volume of unbroken chip inflates, thus increasing the force which contributes to cutting edge deformation, which is why the smaller depth of cut contributes to better surface quality.

Although previous studies report the importance of cutting speed on the activation of tool wear mechanisms, its diminished impact on surface roughness in this study indicates that during the cutting process the critical tool wear was not reached. As the cutting speed increases, surface quality gets better due to lesser cutting force, which ultimately leads to minimization of vibrations.

Approach angle impacts the length of cutting edge in contact with the workpiece, and influences the cutting force distribution, i.e., the load forces on the workpiece. At lower inclination angles cutting force is distributed over a longer cutting edge portion, thinner chip is generated at the equal tool feed, while the concentrated tool insert wear is reduced. As the inclination angle increases, feed resistance goes up while the penetration force goes down, thus reducing the risk of vibrations.

Finally, the cutting inserts with the positive basic geometry, used in this study, contributed to smaller cutting forces, while at the same time reducing the risk of vibrations. Smaller cutting forces induce less vibration which positively impacts the surface quality. High temperatures which are present within the machining zone, can soften the material, while the stimulated shearing overtakes the ploughing. In combination with smaller cutting forces, higher shearing and lower ploughing positively impact tool stability which also favours the surface quality. By reducing the friction, the CVD coating also reduces the heat generated in the machining zone. As the result, one observes smaller thermal loads on the cutting tool inserts, which, in turn, leads to absence of additional tool wear mechanisms which are the result of high temperatures, such as the thermal cracks, built-up edges, etc. All this contributed to increased tool life and higher surface quality after the finishing turning. It should also be noted that the chip breakers used in the experiment increased the efficiency of chip breaking, which allowed broken chip to be the dominant form of chip in the process.

As mentioned before, the confirmation experiments were conducted with the theoretically optimized settings which allowed generation of minimum surface roughness. Mean percent error of the confirmation experiment equals 2.58 %, while the mean absolute error is 0.006 μm. The small percent and mean absolute errors additionally emphasize the practical application potential of the proposed model. In fact, the absolute error on the 10^{-3} µm order of magnitude have practically no impact on the surface roughness. Moreover, this error is also practically beyond the accuracy of the conventional measuring instrumentation used in surface roughness experiments.

5. CONCLUSION

Numerous complex phenomena are present during the turning process. In interaction with a large number of process input variables, these phenomena have a significant impact on surface roughness. In order to overcome the discussed problems, this experimental study suggests the empirical model which is based on three process- and four tool geometry parameters which are vital to the process of finishing turning.

Based on the results from this study, following conclusions emerge:

- The 27 runs in the A-optimal design of experiment, performed by finishing turning with the three numerical and four categorical factors, yielded mean arithmetic surface roughness within the 0.33 µm do 4.98 µm range. The obtained values of *Ra* are lower than the range characteristic for typical turning processes *Ra* = 0.8-6.3 µm [35]. The minimal value of *Ra* shows it is possible to obtain extremely high surface quality and eliminate the need for subsequent machining operations, which, in turn, reduces machining time and costs.
- In this experiment, surface roughness improves with the reduction of feed, depth of cut and cutting insert inclination angle, while the cutting speed, corner radius, rake and approach angle should be kept at their high levels. Although feed and corner radius had a dominant impact on the surface roughness, the contribution of the remaining parameters could not be neglected.
- The empirical model proposed in this study allows modelling and optimization of the finishing turning process, through the selection of the proper levels of seven input variables. This yields a minimized mean surface roughness, *Ra* = 0.238 µm, within a narrow 95 % confidence interval which results in small prediction errors.

Future investigations shall be directed towards evaluation, modelling, and optimization of other operations, and shall include additional input variables (clearance angle, insert size, insert shape, chip breaker type, coating type), as well as the prediction and optimization of several output variables (dimensions, tool wear, energy consumption).

ACKNOWLEDGEMENT

The results presented in this paper are obtained in the framework of the project entitled Innovative scientific and artistic research from the FTS domain (Grant number 451-03-68/2022-14/200156) funded by the Ministry of Education, Science and Technological Development of Republic of Serbia.

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