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OPTIMIZATION OF HARD TURNING PROCESS PARAMETERS WITH PCBN TOOL BASED ON THE TAGUCHI METHOD

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Preliminary notes

In this paper, the Taguchi method is applied to find optimum process parameters for hard turning of hardened steel AISI 4142 using PCBN tool. Orthogonal design (L9 (3^4)), signal-to-noise ratio (*S/N*) and analysis of variance (ANOVA) are applied to study performance characteristics of cutting parameters (cutting speed, feed and depth of cut) with consideration of surface roughness. Significant factors affecting surface roughness were identified, and the optimal cutting combination was determined by seeking the best surface roughness (response) and signal-to-noise ratio. Using multiple regression the exponential, first order linear and second order prediction models were obtained to find the correlation between surface roughness and independent variables. Finally, confirmation tests verified that the Taguchi design was successful in optimizing turning parameters for surface roughness.

Keywords: *ANOVA, hard turning, regression analysis, surface roughness, Taguchi method*

Optimizacija parametara procesa tvrdog tokarenja PCBN alatnim pločicama temeljem Taguchijeve metode

Prethodno priopćenje

U ovom radu, primijenjena je Taguchijeva metoda za pronalaženje optimalne razine parametara procesa tvrdog tokarenja čelika AISI 4142 koristeći PCBN alatne pločice. Ortogonalni plan (L9 (3^4)), omjer signal - šum (*S/N*) i analiza varijance (ANOVA) primijenjeni su u istraživanju utjecaja parametara obrade (brzine rezanja, posmaka i dubine rezanja) na hrapavost obrađene površine. Utvrdilo se signifikantne faktore koji utječu na hrapavost obrađene površine, i definiralo optimalne razine parametara obrade pronalaženjem najniže hrapavosti obrađene površine (odziva) i najpogodnijeg omjera signal – šum. Koristeći višestruku regresiju dobiveni su eksponencijalni model, linearni polinomski model prvog reda i polinomski model drugog reda da bi se utvrdila korelacija između hrapavosti obrađene površine i nezavisnih varijabli. Na kraju, test provjere je potvrdio da je Taguchijev plan uspješan u optimiziranju parametara tokarenja s obzirom na hrapavost obrađene površine.

Ključne riječi: *ANOVA, hrapavost obrađene površine, regresijska analiza, Taguchijeva metoda, tvrdo tokarenje*

1 Introduction

Hardened steels are machined by grinding process in general, but grinding operations are time consuming and are limited to the range of geometries to be produced. Improvements in machine tool rigidity and the development of ceramic and CBN cutting tools allow the machining of hardened steel on a lathe or turning center [1, 2, 3]. Hard turning is defined as the process of single point cutting of part pieces that have hardness values over 45 HRC. Since surface finish with the *Ra* roughness parameter about 0,2÷0,3 μm or *Rz* parameter of 1÷2 μm can be achieved hard turning provides an alternative to grinding for some applications. Surface roughness is a widely used index of product quality and in most cases a technical requirement for mechanical products [4, 5, 6]. The aim of this research is to analyse dependence of the surface roughness *Ra* on three cutting parameters, namely the cutting speed v_c, the feed f and the depth of cut a_p, in hard turning operation with Taguchi method and to find optimal level of the parameters. Selection of optimal cutting parameters is necessary in order to achieve optimal values of surface roughness. The optimal level design parameters are used to predict and verify the improvement of the quality characteristic. Prediction models of surface roughness considering the main cutting parameters for hard turning of AISI 4142 hardened steel with PCBN tool are also developed using regression analysis. CBN and PCBN are ideal cutting tool materials for the hard finishing of parts above 55 HRC. An analysis of results obtained by Taguchi method and multiple regression was carried out. Based on this analysis, valuable remarks about the presented optimisation approach are pointed out in the conclusion of this study.

2 Conditions of the experiments

Experimental research was performed on CNC lathe machine "Safop-Leonard 60/1800". The material used throughout this work was an AISI 4142 hardened steel bar with 260 mm diameter and 700 mm length. Chemical composition and mechanical properties of AISI 4142 steel are given in Tab. 1 and Tab. 2. The workpiece was heat-treated and quenched with water resulting in a hardness of 55 HRC. Experiments were carried out by external machining turning tool with holder mark PCLNR 3232 P12 and inserts type PCBN X65/2C3 CNGA 120408W T1A. **Gulfcut HWSS** metalworking fluid was used during the experiment in concentration of 6 %. The CBN/TiCN cutting inserts employed in this study contained about 65 % CBN. The average grain size was about 2÷4 μm with metal ceramic binder phase. Thickness of the layer of PCBN on a hard metal base was 0,7÷1,0 mm. Nose radius of cutting insert was 0,8 mm. The work material steel bar was centered and cleaned by removing a 1 mm depth of cut from the outside surface, prior to actual machining tests. Surface roughness measurements were performed with Surtronic 25 Taylor Hobson roughness checker. The surface roughness

Table 1 Chemical composition (wt. %)

Material	C	Mn	Si	Cr	Mo	P	S
AISI 4142	0,41	0,75	0,2	1,05	0,23	<0,035	<0,035

Table 2 Mechanical properties

Material	Tensile strength /MPa	Yield strength /MPa	% of Elongation
AISI 4142	750-900	500	14

measured in the paper is the arithmetic mean deviation of surface roughness of profile *Ra*.

3 Application of robust design of experiment: Taguchi method

The Taguchi design was used to determine optimal cutting parameters and to find the relationships between independent variables and surface roughness. The Taguchi method uses a special design of orthogonal arrays to study the entire parameter space with a small number of experiments only [2, 6, 7, 8]. The experimental results are then transformed into a signal-to-noise (*S/N*) ratio. Taguchi recommends the use of the *S/N* ratio to measure the quality characteristics deviating from the desired values [9, 10]. Usually, there are three categories of quality characteristic in the analysis of the *S/N* ratio, i.e. the-smaller-the-better, the-higher-the-better, and the nominal-the-better. The *S/N* ratio for each level of process parameters is computed based on the *S/N* analysis. Regardless of the category of the quality characteristic, a greater *S/N* ratio corresponds to better quality characteristics. Therefore, the optimal level of the process parameters is the level with the greatest *S/N* ratio. The experiments have been carried out by using the standardized Taguchi-based experimental design, a L9 (3^4) orthogonal arrays, with three levels (coded by: 1; 2 and 3) of three cutting parameters (Tab. 3).

Table 3 Physical and coded values of cutting parameters for robust design of experiment

Symbol	Parameters	Levels		
	Coding – orthogonal array	1	2	3
A	Cutting speed $X_1 = v_c$ /m/min	100	130	160
B	Feed $X_2 = f$ /mm/rev	0,05	0,15	0,25
C	Depth of cut $X_3 = a_p$ /mm	0,1	0,35	0,6

The necessary number of test runs is nine. The last column (for the fourth factor) in the L9 (3^4) orthogonal array is left empty for this specific study. Before each cut, the insert was changed to eliminate the effect of tool wear. To obtain minimal surface roughness, the "smaller is better" quality characteristic for surface roughness must be taken. *S/N* ratio μ is determined according to the following equation:

$$S/N = \mu = -10 \cdot \lg\left(\frac{1}{n}\sum_{i=1}^{n} y_i^2\right), \tag{1}$$

where n is the number of replication and y_i is measured value of output variable.

3.1 Results obtained by Taguchi method

Experimental results, together with their transformations into signal-to-noise ratios are given in Tab. 4.

The influence of each control factor can be more clearly presented with response graphs and response table. A response graph shows the change of the *S/N* ratio when the setting of the control factor is changed from one level to the other (Fig. 1).

The response graphs for surface roughness *Ra* have been shown for all three control factors. The minimal *Ra* is achieved using the cutting parameters where *S/N* ratio is

Table 4 Orthogonal array L9 (3^4) with experimental results and calculated *S/N* ratios

Test No.	A v_c	B f	C a_p	$\overline{Ra}$ /µm	*S/N* ratio /dB
1.	1	1	1	0,3	10,458
2.	1	2	2	0,62	4,152
3.	1	3	3	0,96	0,355
4.	2	1	2	0,374	8,543
5.	2	2	3	0,766	2,315
6.	2	3	1	0,518	5,713
7.	3	1	3	0,488	6,232
8.	3	2	1	0,426	7,412
9.	3	3	2	0,762	2,361

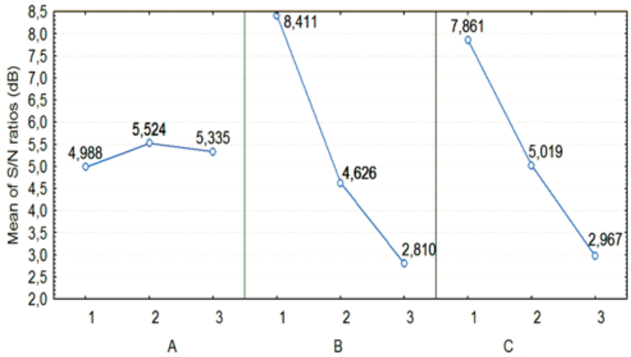

Figure 1 Influence of control factors on S/N ratio

maximal. The slope of the line which connects different parameter levels determines the power of the influence of a control factor. It can be seen from the presented graphs that feed rate has the greatest influence on the surface roughness, followed by depth of cut. Cutting speed has insignificant influence on the surface roughness in hard turnining. The influence of interactions between control factors was neglected here. The *S/N* response table shows the mean of *S/N* ratios for each level of each factor. The table includes ranks based on Delta statistics, which compare the relative magnitude of effects. The ranks indicate the relative importance of each factor to the response and it can be seen from the table that feed rate has the highest rank 1, followed by depth of cut, and finally cutting speed (Tab. 5). The response table and response graph indicate that level 2 for cutting speed, and level 1 for feed rate and depth of cut reduce the variation in the response. These levels produce the highest *S/N* ratios and lowest standard deviations so they are optimal levels of control factors.

Table 5 *S/N* response table for surface roughness

Main control factors	Symbol	Mean *S/N* ratio /dB				
		Level 1	Level 2	Level 3	Max-Min	Rank
Cutting speed v_c /m/min	A	4,988	5,524	5,335	0,536	3
Feed f /mm/rev	B	8,411	4,626	2,810	5,601	1
Depth of cut a_p /mm	C	7,861	5,019	2,967	4,894	2

3.2 Estimation of optimum value of surface roughness

Once the optimal level of the design parameters has been selected, the next step is to predict *S/N* ratio using the optimal level of design parameters. The optimization of cutting parameters inside of offered factors levels, with regard to the criterion "smaller is better", gives the following combination of the cutting parameters which enables minimal surface roughness: v_c = 130 m/min, f = 0,05 mm/rev and a_p = 0,1 mm. The estimated *S/N* ratio $\hat{\eta}$ using the optimal level of the design parameters can be calculated as

$$\hat{\eta} = \eta_m + \sum_{i=1}^{o} (\eta_{im} - \eta_m) \quad (2)$$

where, η_m is the total mean *S/N* ratio, η_{im} is the mean *S/N* ratio at the optimal level, and o is the number of the main design parameters that affect the quality characteristic (Tab. 5). We can derive the expression for surface roughness Eq. (3) from Eq. (1) and calculate the surface roughness at optimal cutting conditions ($\hat{Ra}$).

$$\hat{Ra} = \sqrt{10^{\frac{S/N}{10}}} = 10^{-\frac{S/N}{20}}. \quad (3)$$

The estimated *S/N* ratio is $\hat{\eta}$ =11,22 dB and it was used to calculate optimal surface roughness, $\hat{Ra}$ = 0,275 μm, (Tab. 6). Surface roughness is within class N5, which has a range between 0,2 and 0,4 μm.

Table 6 Optimum levels of control factors

Main control factors	Symbol	Optimum level	Optimum value	Estimated values
Cutting speed v_c /m/min	A	2	130	*S/N*=11,22 dB
Feed f /mm/rev	B	1	0,05	$\hat{Ra}$ =0,275 μm
Depth of cut a_p /mm	C	1	0,1	

The confidence interval (*C.I.*) represents the boundaries on the expected results and is always calculated at a confidence level. The experiment is considered satisfactory when the predicted mean falls within this limit. A confidence interval for the predicted mean on a confirmation run can be calculated using the following equation [10]:

$$C.I. = \pm \left(\frac{F_{\alpha;(1,f_e)} \cdot V_e}{n_{eff}} \right)^{1/2}, \quad (4)$$

where $F_{\alpha(1,fe)}$ is the F value from the F table for factor *DOF* and error *DOF* (f_e) at the desired confidence level $(1-\alpha)$. V_e is the variance of the error term (from ANOVA), and n_{eff} the effective number of replications given by:

$$n_{eff} = \frac{N}{1 + (\text{Total } DOF \text{ associated in the estimate of mean})}, \quad (5)$$

where N is total number of experiments. Total *DOF* associated with the mean = 6 and N = 9 are used to calculate the effective number of replications n_{eff} = 9/(1 + 6) = 1,29. The F value from the F table for f_e = 2 at the confidence level of 85 % is $F_{0,15(1,2)}$=3,5. Using the values V_e = 0,1308 and $F_{0,15(1,2)}$=3,5 the confidence interval is calculated: *C.I.* = ±0,59 dB. The estimated mean *S/N* ratio is $\hat{\eta}$ =11,22 dB. The 85 % confidence interval of the predicted optimal *S/N* ratio is: $[\hat{\eta} - C.I.] < \hat{\eta} < [\hat{\eta} + C.I.]$ i.e. $10{,}632 < \hat{\eta}(\text{dB}) < 11{,}81$. After transformation *C.I.* for optimal surface roughness at the 85 % confidence level is: $0{,}257 < \hat{Ra}(\mu\text{m}) < 0{,}294$. The average result of the confirmation test at the optimum condition is expected to be within 0,257 and 0,294 μm with confidence of 85 %.

3.3 Analysis of the variance

The purpose of the analysis of the variance (ANOVA) is to investigate which design parameters significantly affect the quality characteristic. Tab. 7 shows the results of ANOVA for surface roughness. In addition to degree of freedom, mean of squares (MS), sum of squares (SS), *F*-ratio and *P*-values, contribution (C) associated with each factor was presented. This analysis was performed for a confidence level of 95 %. The *F*-ratio for each design parameters was calculated. $F_{0,05}$ for parameters degree of freedom and error degree of freedom (2,2) is given in Tab. 7. To be significant the calculated *F*-ratio for each design parameter must be greater than $F_{0,05}$ as shown in the ANOVA table. The calculated values of the *F*-ratio showed high influence of the feed rate (187,35>19) and depth of cut (138,57>19) on surface roughness. The contributions are in the following order: feed rate (56,736 %), depth of cut (41,86 %) and then cutting speed (0,214 %). Feed rate and depth of cut are the significant cutting parameters for affecting the surface roughness.

4 Predictive modeling using regression analysis

Multiple regression is used as a model formulation procedure to investigate how control factors (v_c, f, a_p) affect the response of an experiment (*Ra*) and lead to the development of exponential, first-order and second-order prediction models [2, 6, 11]. The set of regression coefficients are unknown parameters and they are estimated by least squares. The functional relationship between

Table 7 ANOVA results for signal-to-noise ratio for surface roughness

Main control factors	Symbol	Degree of freedom DF	Sum of squares (SS)	Mean of squares (MS)	*F*-ratio	$F_{0,05\,(2,2)}$	*P*-value	Contribution, *C* /%
Cutting speed v_c	A	2	0,4429	0,2214	1,69	19	0,371	0,214
Feed f	B	2	48,9911	24,4956	187,35	19	0,005	56,736
Depth of cut a_p	C	2	36,2357	18,1179	138,57	19	0,007	41,860
Error	-	2	0,2615	0,1308	-	-	-	1,190
Total	-	8	85,9313	42,9656	-	-	-	100

surface roughness and independent variables under investigation could be postulated as

$$Ra = C \cdot f^{x} \cdot a_{\mathrm{p}}^{y} \cdot v_{\mathrm{c}}^{z}, \quad (6)$$

where v_c is the cutting speed, f the feed rate, a_p the depth of cut, C is a constant and x, y, z are the exponents and depend on the material, tool and processing conditions. A logarithmic transformation can be applied to convert the non-linear form of equation into the linear form of Eq. (6)

$$\ln Ra = \ln C + x \cdot \ln v_{\mathrm{c}} + y \cdot \ln f + z \cdot \ln a_{\mathrm{p}}. \quad (7)$$

The prediction model of exponential multiple regressions is given by

$$\ln Ra = 1{,}07 - 0{,}091 \cdot \ln v_{\mathrm{c}} + 0{,}4 \cdot \ln f + 0{,}305 \cdot \ln a_{\mathrm{p}}. \quad (8)$$

For the 95 % confidence level the model has coefficient of determination R^2 = 0,987, which means that the model is representative, because it clarifies 98,7 % of all deviations. Standard deviation is S = 0,055. Feed rate and depth of cut are the significant cutting parameters. The first order model equation for surface roughness prediction is given by

$$\ln Ra = 0{,}231 - 0{,}00113 \cdot v_{\mathrm{c}} + 1{,}8 \cdot f + 0{,}647 \cdot a_{\mathrm{p}}. \quad (9)$$

For the 95 % confidence level the model has coefficient of determination R^2 = 96,5 %. Standard deviation is S = 0,051. Second order regression model was also extended from the first order model when considering interaction effects. The second order model equation for the tool life prediction is given by

$$\begin{aligned} Ra &= 0{,}304 - 0{,}0011 \cdot v_{\mathrm{c}} - 0{,}24 \cdot f + 0{,}822 \cdot a_{\mathrm{p}} + \\ &+ 0{,}0106 \cdot v_{\mathrm{c}} \cdot f - 0{,}0027 \cdot v_{\mathrm{c}} \cdot a_{\mathrm{p}} + 1{,}6 \cdot f \cdot a_{\mathrm{p}}. \end{aligned} \quad (10)$$

For the 95 % confidence level the model has coefficient of determination R^2 = 98,7 %. Standard deviation is S = 0,054. The results obtained by a comparison between predicted values of the models developed in the present work (Eqs. (8), (9) and (10)) and the experimentally obtained results for surface roughness are shown in Tab. 8. Prediction models are compared with experimental results and in the presented case show very small deviation of foreseen values. The second order model was found to have better prediction capability, average relative error was 2,83 %. Therefore, the models constructed in the present work could be used to predict the surface roughness of hard turning.

Table 8 Different models results compared with the results of experiment and relative error

Experiment		Exp. model (8)		1st ord. model (9)		2nd ord. model (10)	
Test No.	$\overline{Ra}$ /μm	Ra_{exp} /μm	Rel. error /%	$Ra_{\mathrm{1st.or.}}$ /μm	Rel. error /%	$Ra_{\mathrm{2nd.or.}}$ /μm	Rel. error /%
1.	0,30	0,285	5,00	0,272	9,33	0,298	0,76
2.	0,62	0,647	4,35	0,613	1,13	0,593	4,30
3.	0,96	0,936	2,50	0,955	0,52	0,969	0,93
4.	0,37	0,407	8,82	0,400	6,95	0,410	9,57
5.	0,76	0,745	2,74	0,741	3,26	0,757	1,19
6.	0,51	0,529	2,12	0,597	15,25	0,531	2,57
7.	0,48	0,471	3,48	0,527	7,99	0,481	1,37
8.	0,42	0,423	0,70	0,384	9,86	0,408	4,20
9.	0,76	0,761	0,13	0,725	4,86	0,767	0,60
Average (1÷9)			3,32	-	6,57	-	2,83

5 Analysis of results

Once the optimal level of the design parameters has been selected, the final step is to verify the improvement of the quality characteristic using the optimal level of design parameters. The combination of the optimal levels of all the factors should produce the optimal magnitude of surface roughness (the smallest *Ra*). This conclusion must be further supported through the confirmation run, Tab. 9. The mean result of the confirmation test at the optimum condition is within confidence interval 0,257 $< \hat{R}a(\mu\mathrm{m}) <$ 0,294 as expected. The increase of the *S/N* ratio from the initial cutting parameters to the optimal cutting parameters is 3,49 dB and therefore the surface roughness value is improved by about 50 %. The presented optimisation approach by Taguchi method provides accurate results (as indicated by the confirmation test) with small deviation between each other. Relative error of Taguchi method considering confirmation test is 4,18 %, (Tab. 10). From the analysis of Tab. 10 we can observe that prediction models Eqs. (8)÷(10) correlate surface roughness and cutting parameters with a reasonable degree of approximation. The exponential and second order model have better prediction capability, relative error is 2,44 % for exponential model and 4,88 % for the second order model considering confirmation test.

Table 9 Results of the confirmation experiment for surface roughness

	Initial parameters	Optimal cutting parameters	
		Taguchi method	Confirmation test
Level	A3B2C1	A2B1C1	A2B1C1
Ra /μm	0,426	0,275	0,287
S/N /dB	7,412	11,22	10,9
Improvement of *S/N* ratio=3,49 dB.			

Table 10 Comparison of the results obtained with prediction models, Taguchi method and confirmation test using optimal cutting parameters

	Initial parameters	Optimal cutting parameters				Confirmation test
		Taguchi method	Prediction models			
			Exp. (8)	1st Ord. (9)	2nd Ord. (10)	
Level	A3B2C1	A2B1C1	A2B1C1	A2B1C1	A2B1C1	A2B1C1
Ra /μm	0,426	0,275	0,28	0,239	0,273	0,287
Rel. error /%	-	4,18	2,44	16,72	4,88	-

6 Conclusions

This paper has discussed an application of the Taguchi method for optimizing cutting parameters in hard turning operations and multiple regression is used as a model formulation procedure to investigate how control factors (v_c, f, a_p) affect the response of an experiment (Ra). The aim was to take advantage of the Taguchi method to perform optimization with a small number of experiments and possibility of multiple regression to obtain mathematical models which are a powerful tool to predict response for any of input parameters values within the experimental domain. This is impossible in the Taguchi method because optimal values have to be one of the parameter levels. By using the Taguchi method the number of experiments is drastically reduced. A L9 (3^4) Taguchi orthogonal array, the signal to noise (*S/N*) ratio and the analysis of variance (ANOVA) were used for the optimization of cutting parameters. The experimental results indicate that in this study feed rate exerted the greatest effect on surface roughness, followed by depth of cut. Cutting speed had insignificant influence on surface roughness. The contributions are in the following order: feed rate (56,736 %), depth of cut (41,86 %) and then cutting speed (0,214 %). The estimated *S/N* ratio and *Ra* were calculated using the optimal cutting parameters for surface roughness. The confirmation experiment was conducted and verified the optimal cutting parameters. The mean result of the confirmation test at the optimum condition is within confidence interval $0{,}257 < \hat{R}a\,(\mu m) < 0{,}294$. The experiment is considered satisfactory when the mean result falls within this limit. The improvement of surface roughness from the initial cutting parameters to the optimal cutting parameters is about 50 % suggesting that the Taguchi parameter design is an efficient and effective method for optimizing surface roughness in a hard turning operation. The exponential, first order linear and second order prediction models were obtained using multiple regression. The results obtained by means of prediction models prove that they can be used to predict surface roughness in hard turning, within the experimental domain, with a reasonable degree of approximation.

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