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OPTIMIZATION OF DRY TURNING PROCESS PARAMETERS USING TAGUCHI METHOD COMBINED WITH FUZZY LOGIC APPROACH

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Abstract: *In this paper, Taguchi method combined with fuzzy logic approach was used in order to define dry turning process parameters values that lead to minimal surface roughness. The surface roughness presents one of the most important criterions relating to proper choice of machining parameters during machining. Parameters that were being optimized here are cutting speed (v_c), depth of cut (a_p), feed rate (f) as well as workpiece steel material: St 50-2, C45 and 42CrMo4. The experiments were conducted using Taguchi's design of experiments. Orthogonal array L_9 (3^4) was selected for the four input parameters varied on the three levels. In this study it was found out that Taguchi method and fuzzy logic approach can be successfully employed to determine the optimal turning parameters values and to describe an influence of these parameters on the surface roughness response. Moreover, developed fuzzy logic model can be used for development of expert system that would enable better machining process control.*

Keywords: *dry turning, optimization, parameters, Taguchi, fuzzy logic*

1. INTRODUCTION

Green manufacturing is a basis of sustainable development strategy in machining industry that implies balancing between economical, ecological and sociological segment of production. Green machining in manufacturing industry requires changes in the type and quantity of resources, in the waste treatment, in the control of emissions CO_2, and in the quantity of manufactured products. The main goal of machining process is to get a high quality products in the short time. In achieving of that goal cutting fluids and machining input parameters have a main role. The problem of application conventional cutting fluids during machining processes are human health and environmental pollution problems. The solution in terms of switching to green manufacturing is hidden in application of alternative types of cooling, flushing and lubricating techniques. These techniques are minimum quantity lubrication (MQL), cooling with cold compressed air (CCA), cryogenic cooling (CL) with different gasses, high pressure cooling (HPC), minimum quantity lubrication and cooling (MQLC), near dry machining (NDM) or dry machining by using new cutting tools and coatings. Dry machining is an environmentally friendly technique which is successfully applied in machining processes.

The most important advantages of dry machining are in reducing of disposal and cleaning costs of cutting fluids, reducing of environmental pollution and no danger for health of operators. The elimination of CFs involves the loss of their positive effects, such as cooling, lubrication and chip flushing. Development of production in terms of transition to dry machining is followed by development of new cutting tool materials. Advanced cutting tool materials and tool coatings are necessary during dry machining but they are very expensive and increase the total machining costs. Some of these materials are: sintered diamond, sintered CBN, ceramics (Al_2O_3), cermets, cemented carbides etc. Coatings of cutting tools in dry machining replace function of conventional cutting fluids in the terms of decrease friction and temperature in the cutting zone. The lubricating function of coatings in dry machining can be replaced with the soft coatings or so-called self-lubricating coatings like molybdenum disulfide (MoS_2) or tungsten carbide/carbon (WC/C).

In each machining process so even in dry machining a surface roughness is one of the most used outputs that defines a quality of the final product. In this paper an investigation of the influence of input process parameters such as cutting speed, depth of cut, feed rate and type of workpiece material on the surface roughness output was conducted. Combined approach of Taguchi method and fuzzy logic technique was used to describe an influence of each process parameter on the surface roughness response and to define parameters values that lead to minimal surface roughness.

2. EXPERIMENTAL PROCEDURE

Experiments in this paper were carried out on a conventional PA-501A Potisje lathe with the ISO CNMG 120408-WG coated carbide insert of cutting tool. All experimental tests were carried out by dry machining. Machining process parameters that were considered in the experimentations are: cutting speed (v_c), depth of cut (a_p), feed rate (f) and type of workpiece material. These parameters were varied in the following ranges: cutting speed 58-162 m/min, depth of cut 1-3 mm, feed rate 0.107-0.321 mm/rev on three levels and workpiece material as follows St 50-2, C45, 42CrMo4 (Table 1). Measurements of the surface roughness parameter *Ra* were performed on a Perthometer M1 type (Mahr) profilometer, at three different locations. Experimental design matrix was defined in accordance with the standard Taguchi L9 (3^4) orthogonal array (Table 2). Experimental setup is presented in Figure 1.

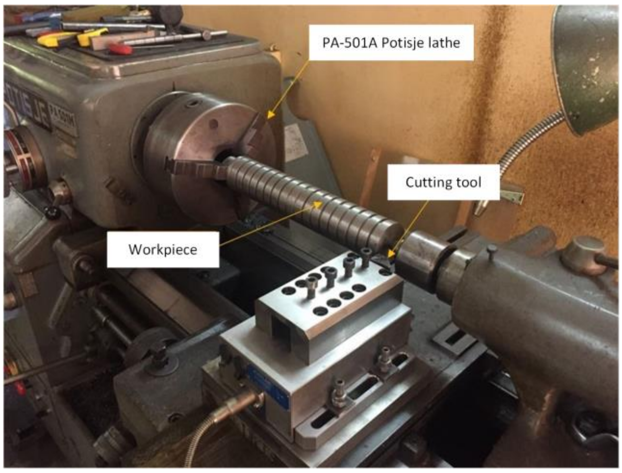


Figure 1. Experimental setup for dry turning

Table 1. Dry turning process parameters levels

Parameter/Level	Symbol	Level		
		1	2	3
Cutting speed v_c (m/min)	A	58	110	162
Depth of cut a_p (mm)	B	1	2	3
Feed rate f (mm/rev)	C	0.107	0.214	0.321
Workpiece material	D	St 50-2	C45	42CrMo4

3. METHODOLOGY

3.1 Taguchi method

Taguchi method is a simple and powerful tool for modelling, analysis and optimization of the machining process. In this method experimental data need to be transformed into signal-to-noise (*S/N*) ratio as the measure of the output quality characteristic. By *S/N* ratio it is possible to evaluate the effect of changing a particular input parameter on the analyzed process response. Depending on the criterion for the quality characteristic to be optimized, the *S/N* ratio can be divided into: smaller-the-better, larger-the-better, and nominal-the-better. Regardless of the category of the process response, the larger *S/N* ratio corresponds to the better process performance characteristic. Accordingly, process parameters levels that lead to optimal response have the highest *S/N* ratio values. Optimization of process response is performed by using the analysis of means (ANOM) and analysis of variance (ANOVA). The last step in the Taguchi optimization is conducting of the confirmation experiment that should verify optimal settings of variable process parameters [1, 2, 3].

Table 2. L9 orthogonal array and surface roughness results

Trial No.	Input parameters				Outputs	
	A	B	C	D	*Ra* (µm)	*S/N* (dB)
1.	1	1	1	1	1.88	-5.483
2.	1	2	2	2	1.17	-1.363
3.	1	3	3	3	1.36	-2.670
4.	2	1	2	3	0.95	0.445
5.	2	2	3	1	1.1	-0.827
6.	2	3	1	2	1.42	-3.045
7.	3	1	3	2	1.55	-3.806
8.	3	2	1	3	1.52	-3.636
9.	3	3	2	1	1.16	-1.289

3.2 Fuzzy logic

Fuzzy logic is an artificial intelligence method that is very useful for modelling complex processes where limited and imprecise informations and numerical data do not allow development of accurate mathematical models by using classical methods such as regression analysis. In these cases a fuzzy logic provides a way to better understand the process behaviour by allowing the functional mapping between input and output observations [4, 5]. Each fuzzy system consists of four components: the fuzzification module, the fuzzy inference module and the knowledge base and the defuzzification module. Fuzzification module converts numerical input data into linguistic variables by using different membership functions. There are various membership functions such as triangular, trapezoidal, Gaussian etc. These functions define how each point in the input and output space is mapped to a degree of membership value between 0 and 1. Fuzzy inference module uses knowledge base of membership functions and fuzzy IF-THEN rules to perform fuzzy reasoning and generate fuzzy linguistic output variables for corresponding inputs. Finally, the defuzzification module converts the aggregated fuzzy outputs into a non-fuzzy values [4, 5, 6].

4. RESULTS AND DISCUSSION

The process response values for all 9 experiments are used to calculate *S/N* ratio. In this case the goal is a minimization of the surface roughness and because of that *S/N* ratio smaller-the-better was used in calculations. Smaller-the-better *S/N* ratio can be defined as:

$$S/N = \eta = -10\log_{10}\left(\frac{1}{n}\sum_{i=1}^{n} y_i{}^2\right) \qquad (1)$$

where is *S/N* - signal-to-noise ratio, *n* - number of repetitions of the experiment, y_i - measured values of quality characteristic.

To analyze the effects of process parameters on surface roughness a main effects plot was generated. Main effects plot for S/*N* ratio of surface roughness is presented in Figure 2. Greater inclination of input parameter line defines a higher influence of that parameter on the surface roughness. Difference between maximal and minimal average of *S/N* ratio values determines the rank of parameters that affects the process response *Ra*. These values are listed in Table 3.

As it was already mentioned, the highest values of *S/N* ratio define input process parameters levels that together lead to the best process response characteristic. Based on

Figure 2 and Table 3 the optimal setting of process parameters that results with minimal surface roughness is identified as cutting speed 110 m/min, depth of cut 2 mm, feed rate 0.214 mm/rev and workpiece material 42CrMo4, represented as $A_2B_2C_2D_3$. This is marked in bold font in Table 3.

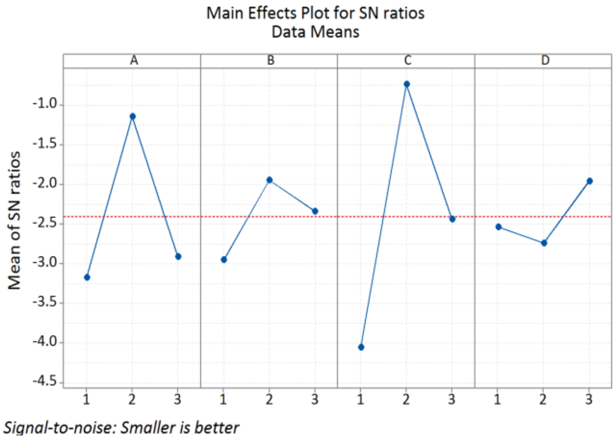


Figure 2. Main effects plot for *S/N* ratios of surface roughness

Table 3. Response table for *S/N* ratio, smaller is better

Level	Parameters			
	Cutting speed (v_c) A	Depth of cut (a_p) B	Feed rate (*f*) C	Workpiece material D
1	-3.1726	-2.9481	-4.0553	-2.5334
2	**-1.1427**	**-1.9428**	**-0.7358**	-2.7387
3	-2.9109	-2.3352	-2.4351	**-1.9540**
Delta	2.0299	1.0053	3.3195	0.7847
Rank	2	3	1	4

To estimate the significance of input parameters on surface roughness, analysis of variance (ANOVA) was performed. Because the experimentation with 4 parameters at 3 levels by using Taguchi L_9 OA does not provide enough data, firstly ANOVA pooling should be conducted. ANOVA pooling is a process of revision and re-estimation of ANOVA results in order to ignore an insignificant parameter whose contribution is less [7, 8]. In this case, from the Table 3 it is evident that workpiece material has the smallest influence on *S/N* ratio of surface roughness. Therefore, ANOVA pooling was done by exception that parameter (Table 4). From the pooled ANOVA it is obvious that feed rate is the most influential parameter that contributes towards *S/N* ratio by 62.67%. It is followed by cutting speed with contribution of 27.73% and depth of cut of 5.84%. This analysis was carried out in the MINITAB statistical software.

Table 4. ANOVA for *S/N* ratio of surface roughness (after pooling)

Source	DF	SS	MS	F	%
A	2	7.3153	3.6576	7.36	27.73
B	2	1.5402	0.7701	1.55	5.84
C	2	16.5316	8.2658	16.64	62.67
Error	2	0.9935	0.4968		3.77
Total	8	26.3805			

In the final step of Taguchi method it is obvious to conduct confirmation experiment to verify optimal process parameters settings ($A_2B_2C_2D_3$). Predicted and experimentally observed values of surface roughness at the optimum levels of process parameters are shown in Table 5.

Table 5. Results of confirmation experiment

	Taguchi optimal parameters settings			
	Prediction	Experiment		
Parameters levels	$A_2B_2C_2D_3$	$A_2B_2C_2D_3$		
Surface roughness *Ra* (μm)	0.753	*Ra1*	*Ra2*	*Ra3*
		0.76	0.73	0.77

Furtherly, in order to develop an expert system that would be used for better control of machining process a fuzzy logic modelling of surface roughness was performed. Mamdani fuzzy inference system was used to define relationship between variable (the most influential) process parameters (v_c, a_p and *f*) and surface roughness response. Structure of developed fuzzy logic system is shown in Figure 3.

For each input in fuzzy logic system three Gauss membership functions were used: low (L), medium (M) and high (H). On the other side six Gauss membership functions were used to describe an output of fuzzy logic system: low (L), low-medium (LM), medium (M), medium-high (MH) high (H) and very high (VH). These functions are shown in Figure 4.

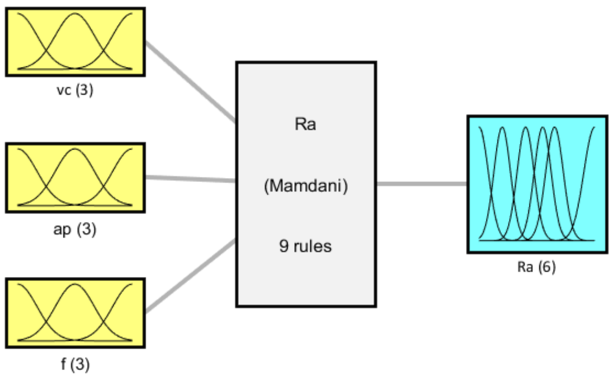
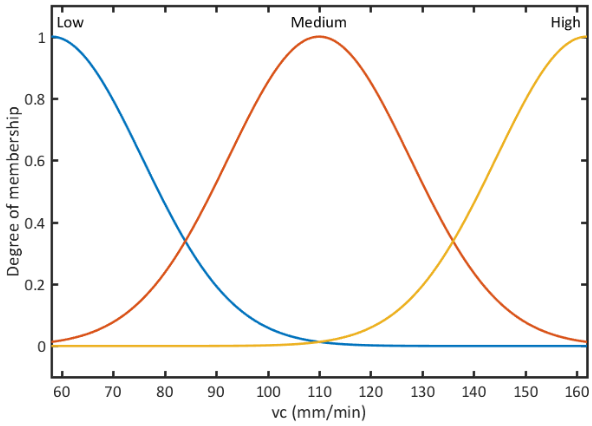
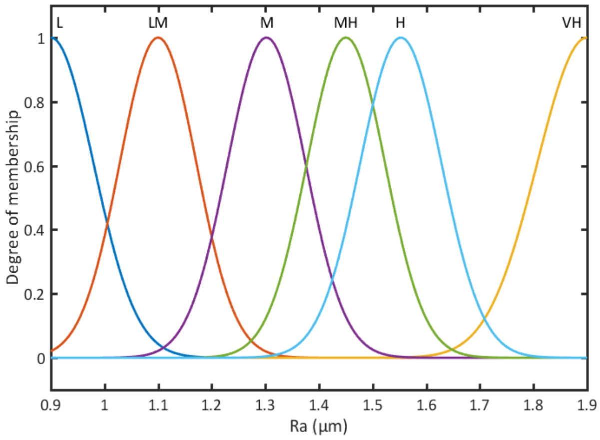


Figure 3. Structure of three inputs and one output fuzzy logic system



a)



b)

Figure 4. Membership functions used for a) inputs (v_c, a_p, f), b) output (Ra)

To perform reasoning fuzzy logic system uses a set of fuzzy IF-THEN rules. In this case a set of nine IF-THEN rules were created to establish a relations between inputs and output. These rules are shown in Figure 5.

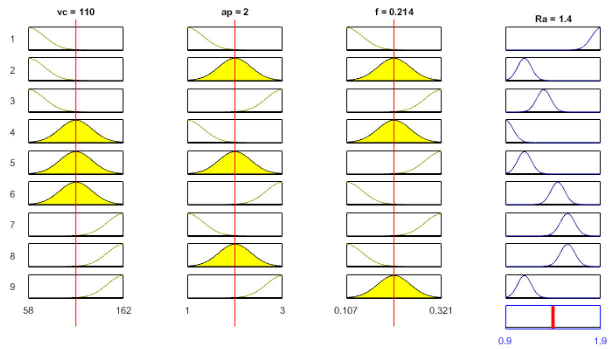


Figure 5. Graphical representation of fuzzy IF-THEN rules

Fuzzy inference process was conducted using MATLAB R2015 software toolbox with the following settings: and method: min, or method: max, implication: min, aggregation: max, defuzzification method: centroid.

Defuzzification module of developed fuzzy logic system converted fuzzy values of *Ra* into a non-fuzzy values. In order to verify prediction accuracy of generated fuzzy logic model, experimental and predicted values of surface roughness were compared. Mean absolute percentage error (MAPE) was used as comparison measure. MAPE of 3.14% proves a good prediction accuracy of developed fuzzy logic model. Comparison results, experimental and predicted surface roughness values and MAPE are shown in Figure 6.

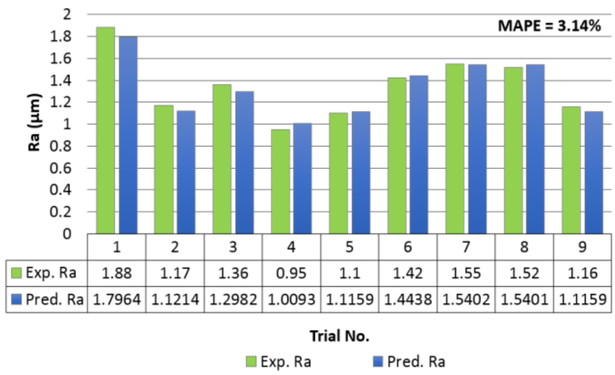
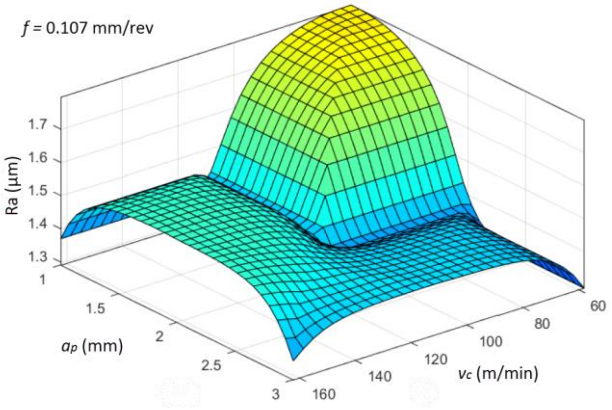
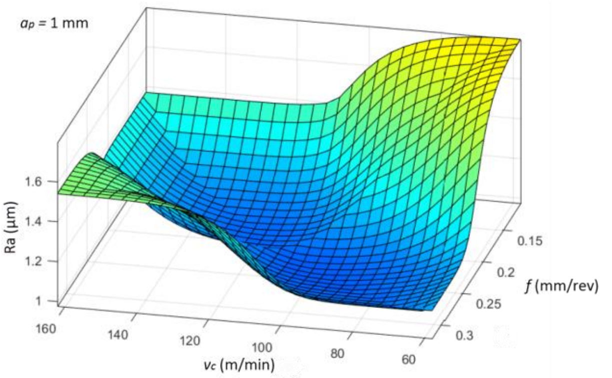


Figure 6. Comparison between experimental and predicted surface roughness values

Based on the developed and validated fuzzy logic model corresponding surface plots that show influence of input process parameters on the surface roughness were created and presented in Figure 7.



a)



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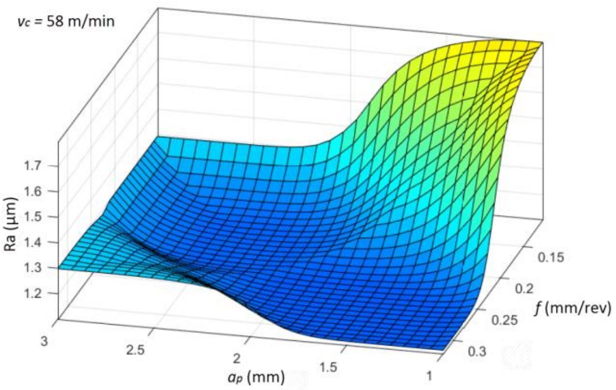

c)

Figure 7. Effects of process parameters on surface roughness response

5. CONCLUSION

This paper presents an application of combined Taguchi-fuzzy logic approach for the optimization and analysis of surface roughness in dry turning machining process. Four different process parameters: cutting speed, depth of cut, feed rate and workpiece material were considered in experimentation according to Taguchi L_9 orthogonal array. From the conducted research, the following conclusions can be drawn:

- feed rate and cutting speed are the most significant parameters that affect the surface roughness variation, whereas the influence of the depth of cut and workpiece material is much smaller,
- it was observed that the cutting speed should be kept at the level 110 m/min, depth of cut 2 mm, feed rate 0.214 mm/rev and workpiece material should be 42CrMo4 to obtain minimal surface roughness,
- fuzzy logic method presents a good mechanism to describe an influence of significant variable dry turning process parameters on the surface roughness and to create an expert system that can be used furtherly in new experimentations and for better machining process control.

REFERENCES

[1] P. Ross: *Taguchi techniques for quality engineering*, McGraw Hill, 1988.

[2] M. Radovanović, L. Slatineanu, P. Janković, D. Petković, M. Madić: Taguchi Approach for the Optimization of Cutting Parameters in Finish Turning of Medical Stainless Steel, Applied Mechanics and Materials, Trans Tech Publications, Switzerland, Vol. 809-810, pp. 153-158, 2015.

[3] M. Madić, M. Radovanović, L. Slatineanu: Surface roughness optimization in CO_2 laser cutting by using Taguchi method, U.P.B. Sci. Bull., Series D, Vol. 75, No. 1, pp. 97-106, 2013.

[4] S. Sivarao, P. Brevern, N.S.M. El-Tayeb, V.C. Vengkatesh: GUI based Mamdani fuzzy inference system modelling to predict surface roughness in laser machining, International Journal of Electrical and Computer Sciences, Vol. 9, No. 9, pp. 37-43, 2009.

[5] M. Madić, M. Radovanović, Ž. Ćojbašić, B. Nedić, M. Gostimirović: Fuzzy Logic Approach for the Prediction of Dross Formation in CO_2 Laser Cutting of Mild Steel, Journal of Engineering Science and Technology Review, Vol. 8, No. 3, pp. 143-150, 2015.

[6] C.Z. Syn, M. Mokhtar, C.J. Feng, Y.H.P. Manurung: Approach to prediction of laser cutting quality by employing fuzzy expert system, Expert Systems with Applications, Vol. 38, No. 6, pp. 7558-7568, 2011.

[7] N. Senthikumar, J. Sudha, V. Muthukumar: A grey-fuzzy approach for optimizing machining parameters and the approach angle in turning AISI 1045 steel, Advances in Production Engineering & Management, Vol. 10, No. 4, pp. 195-208, 2015.

[8] Das Biswajit, S. Roy, R.N. Rai, S.C. Saha: Application of grey fuzzy logic for the optimization of CNC milling parameters for Al-4.5%Cu-TiC MMCs with multi-performance characteristics, Engineering Science and Technology, an International Journal, Vol. 19, No. 2, pp. 857-865, 2016.