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SURFACE ROUGHNESS MODELING OF CBN HARD STEEL TURNING

Study in the paper investigate the influence of the cutting conditions parameters on surface roughness parameters during turning of hard steel with cubic boron nitrite cutting tool insert. For the modeling of surface roughness parameters was used central compositional design of experiment and artificial neural network as well. The values of surface roughness parameters Average mean arithmetic surface roughness (R_a) and Maximal surface roughness (R_{max}) were predicted by this two-modeling methodology and determined models were then compared. The results showed that the proposed systems can significantly increase the accuracy of the product profile when compared to the conventional approaches. The results indicate that the design of experiments modeling technique and artificial neural network can be effectively used for the prediction of the surface roughness parameters of hard steel and determined significantly influential cutting conditions parameters.

Keywords: RSM, neural network, surface roughness, hard steel

1. Introduction

To increase quality of finished products for in manufacturing processes and systems is defined by how closely the finished product fit to certain specifications, including dimensions and surface roughness quality. Surface roughness quality is defined by the combination of surface finish, surface texture, and surface roughness parameters. The commonest parameters for determining surface roughness quality are Average mean arithmetic surface roughness (R_a) and Maximal surface roughness (R_{max}), *Quintana etc*.

Manufacturing processes do not allow to achieve the theoretical surface roughness due to effects appearing on machined surfaces and mainly generated by deficiencies and imbalances in the machining process. Due to these influences to know the surface quality, it is necessary to employ theoretical models making it feasible to do predictions influence parameters in function of response parameters *Sivarao etc*, *Mankova etc*.

Recently, some investigations in applying the basic artificial intelligence approach to model of machining processes, have appeared in the literature. There concludes that the modeling of surface roughness in machining processes has mainly used Artificial Neural Networks and fuzzy set theory *Choudhary etc Grzenda etc*. Average mean arithmetic surface roughness, Ra using artificial neural network was predicted in *Balic, Korosec, Azouzi, M. Gullot*..

Accurate modeling and prediction of surface roughness by computer vision in turning operations using an adaptive neuro-fuzzy inference system was presented in study *Ho etc*. Research of the influence of machining parameters combination to obtain a good surface finish in turning and to predict the surface roughness values using fuzzy modeling is presented in *Rajasekaran*. Also, may notice that the neural network used in the study, where the enabling resolution of the problem that is difficult to define and mathematically model. This can be seen in the work where the neural network was based on the face milling machining processes, where is aimed to produce the relationship of cutting force versus instantaneous angle of tool rotation *Savković etc*. Application of fuzzy logic and regression analysis for modeling surface roughness in face milling was in paper *Kovac etc*.

In this paper, cutting speed, feed and depth of cut as machining regime parameters were selected for input parameters. For modeling of surface roughness parameters R_a and R_{max} used was Response surface methodology and artificial neural network models were developed.

2. Experimental procedure and material

Machine tool for machining tests was the universal lathe. In the study was used interchangeable insert of CBN (cubic boron nitrite) CNMA 120404 ABC 25/F producer ATRON Germany. For this insert sed was appropriate insert holder for external processing PCLNR 25 25 M16.

The cutting tips was according to DIN 4983 the geometry, as follows: the shape of the plate C → rhomb; the rake angle N → = 0, C → = 7; tolerance class M; Type of tile → with opening A, W and G; length of cutting blade → 12.7 mm (12); cutting edge thickness → 4.76 mm (04); radius of tool tip → 0.4 mm (04). All inserts have a rake angle (0°).

During the study variation of the input model parameters (cutting regime) was performed according central compositional factorial experimental design in 5 levels. This mean values for all input parameters between the two adjacent levels was the geometric mean of these values. Selected levels of input factors and coded values are shown in Table 1.

Workpiece material was steel Č3840 (90MnCrV8). Before the experimental performance the workpiece was, machined to cross-section of Ø34 mm and length 500 mm. Before machining start it was necessary to remove a certain layer of material in order to avoid throwing-ovality and the results were more reliable. The length of the bar of 500 mm, was divided into 24 fields with a length of 10 mm on which the longitudinal cutting was performed. Each field on workpiece was planned for the measurement of one experimental point. Workpiece was than thermally whose hardness after heat treatment was 55 HRC. Cutting without the presence of cooling and lubricating agents was provided

Table1 – Levels of experimental input factor

Factor Levels	Cutting speed v (m/min)	Feed f (mm/rev)	Dept of cut a (mm)
Highest +1.41	180	0,250	0,70
High +1	160	0,200	0,50
Middle 0	120	0,100	0,22
Low -1	90	0,050	0,10
Lowest -1.41	80	0,045	0,07

Measuring the surface roughness parameters with the Talysurf 6 measuring device was done. After processing by a computer, the results, was printing or writing on screen. The personal computer was connected to the Talysurf-6 measuring device using a serial connection COM-3. Instead of the printer, a computer was connected with a special adapter with a measuring machine Talysurf 6. The basic parts of the measuring device Talysurf-6 are shown in Figure 1.

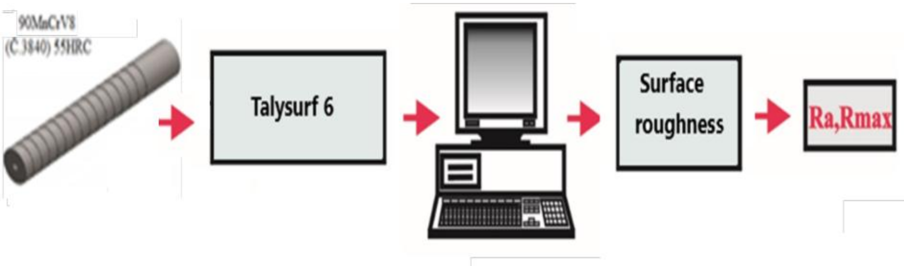

Figure 1 – Surface roughness measurement system Talysurf-6 connected with computer

The measured was values of surface roughness parameters: R_a, R_{max}. The measurement results of these parameters and estimated values by central compositional three factorial models are given in Table 2.

Table 2 – The measurement and modeled results - Input parameters

No.	Factor			R_i measured		R_i RSM Model		R_i Neural network	
	v [m/min]	f [mm/rev]	a [mm]	R_a [µm]	R_{max} [µm]	R_a [µm]	R_{max} [µm	R_a [µm]	R_{max} [µm
1	90	0,05	0,10	0.67	3.9	0.68	3.80	0.66940	3.9250
2	160	0,05	0,10	0.59	3.4	0.63	3.63	0.61679	3.2999
3	90	0,20	0,10	0.79	4.2	0.90	4.68	0.76891	4.4901
4	160	0,20	0,10	0.69	3.6	0.84	4.47	0.90851	2.9274
5	90	0,05	0,50	0.62	3.5	0.75	4.12	0.63529	3.4790
6	160	0,05	0,50	0.71	4.4	0.70	3.94	0.70234	4.3468
7	90	0,20	0,50	0.78	3.9	1.00	5.08	0.77812	3.8940
8	160	0,20	0,50	0.69	3.8	0.93	4.85	0.66813	3.8180
9	120	0,10	0,22	0.93	4.7	0.79	4.29	0.88270	3.9597
10	120	0,10	0,22	0.88	3.9	0.79	4.29	0.87679	3.9147
11	120	0,10	0,22	0.83	4.7	0.79	4.29	0.87099	3.8716
12	120	0,10	0,22	0.9	4.4	0.79	4.29	0.86532	3.8309
13	80	0,10	0,22	1.02	5.6	0.83	4.43	1.02192	5.6070
14	180	0,10	0,22	0.91	4.6	0.76	4.16	0.93119	4.63908
15	120	0,045	0,22	0.87	4.7	0.68	3.81	0.86870	4.7078
16	120	0,25	0,22	1.31	6.7	0.96	4.92	1.31268	6.6933
17	120	0,10	0,07	0.58	3.5	0.74	4.05	0.58573	3.4854
18	120	0,10	0,70	0.76	4.2	0.86	4.55	0.86198	4.7684
19	80	0,10	0,22	1.03	5	0.83	4.43	1.022	5.5707
20	180	0,10	0,22	0.92	5	0.76	4.16	0.9461	4.7089
21	120	0,045	0,22	0.54	3.1	0.68	3.81	0.6721	3.7334
22	120	0,25	0,22	1.21	6.6	0.96	4.92	1.3070	6.6211
23	120	0,10	0,07	0.59	3.5	0.74	4.05	0.5851	3.5764
24	120	0,10	0,70	0.76	4.2	0.86	4.55	0.8574	4.7724

In table 3 are given results of dispersion analyses of implementation of central composition factorial experimental plan: adequacy of models and significance of input parameters.

Table 3 – Adequacy of models and significance of parameters

Model adequacy		R_a	R_{max}
		Fa=4,2921	Fa=3,0585
Significance of parameters	F_{ro}	96,68	3564,19
	Fr1 (v)	1,55 (*)	0,59 (*)
	Fr2 (f)	24,00	12,08
	Fr3 (a)	3,33 (*)	1,82 (*)

Table values for significance: $F_{ri} > F_t$ = 6,61; For adequacy: $F_a < F_t$ = 4,47; (*) No significant parameters

3. Artificial neural network modelling

Artificial neural network (ANN) modeling method is becoming useful as the alternative approach to conventional techniques, or as the component of integrated systems. It is an attempt to predict, within a specialized software, the multiple layers of a number of elementary units called neurons. The MATLAB software, Neural Network Toolbox function, was used to create, train, validate, and predict the different ANNs reported in this research.

In this work, one of the most popular feed-forward networks was selected. This network is a multi-layer architecture proving to be an excellent universal approximation of nonlinear functions. The feed-forward neural network was trained by TRAINLM algorithms. The TRAINLM is a network training function that updates weight and bias values to Levenberg-Marquardt optimization.

Learning is a process by which the free parameters of the neural network are adapted through a continuous process of simulation by the environment in which the network is embedded. The learning function can be applied to individual weights and biases within the network. The LEARNGDM learning algorithms in feed-forward networks are used to adapt networks. Gradient descent method (GDM) was used to minimize the mean squared error between the network output and the actual error rate. It trains the network with gradient descent with the momentum back-propagation method. The back-propagation learning in feed-forward networks belongs to the real of supervised learning, in which the pairs of input and output values are fed into the network for many cycles, so that the network 'learns' the relationship between the input and the output.

For this study, feed-forward network was selected since this architecture interactively creates one neuron at a time. This is an optimization procedure based on the gradient descent rule which adjusts the weights of the network to reduce the system error is hierarchical. The network always consists of at least three layers of neurons: the input, output, and middle hidden layer neurons. The input layer has inputs, which are: v, the cutting speed (m/min); f, the feed (mm/rev); and a, the depth of cut (mm). The outputs are the values of machined surface roughness parameters: arithmetic mean roughness R_a and the maximal roughness high R_{max}. These parameters were set to be modeled by the artificial neural network performance. Characteristic of the used neural network: the number of hidden layers is 12, the number of iterations is 100 and the number of neurons in the hidden layer is 20.

In this study, a part of the experimental data was used for training and the remaining data was used for testing the network. Each input has an associated weight that determines its intensity. The neural network can be trained to perform certain tasks where the data is fed into the network through an input layer.

This is processed through one or more intermediate hidden layers and finally it is fed out to the network through an output layer as shown in Fig. 2. It must be highlighted that the best network architecture is reached by trial and error after considering different combinations of the number of neurons in the hidden layer, the number of hidden layers, spread parameter, and learning rate, depending on the type of neural network being used.

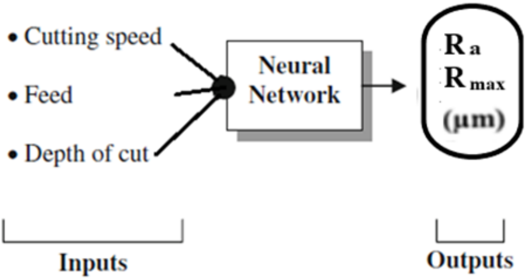

Figure 2 – Network input and output layer

3. Results and discussions

Equations for surface roughness modeling by design of experiment determined by central compositional plan.

$$R_a = 2{,}5258 \cdot v^{-012398} \cdot s^{0{,}2017} \cdot a^{0{,}06486}, \qquad (1)$$

$$R_{max} = 9{,}5757 \cdot v^{-0{,}7596} \cdot s^{0{,}14995} \cdot a^{0{,}0512}.$$

As mentioned before, neural network modeling was used for analysis and optimization of surface roughness in turning process. The obtained results of neural network model are given in the Table 5, side by side with the obtained experimental results. For reduction of a deviation, is needed to increase the number of inputs.

Calculation of percental deviation E for measured and model surface roughness values was performed according next formula:

$$E = \frac{\left| Ri_{\exp} - Ri_m \right|}{Ri_{\exp}} \cdot 100\%,$$

where are: Ri_{exp}- experimental value, Ri_m- model value**.**

Calculated percental deviation for first 18 experimental points are for Ra E=4.30 and for Rmax E=5.19.

Table 5 – Experimental values and values obtained by neural network with percentage deviation for 6 testing points

No.	Factor			R_i - experimenal roughness		R_i - modeled roughness	
	v [m/s]	s [mm/rev]	a [mm]	R_a [μm]	R_{max} [μm]	R_a [μm]	R_{max} [μm]
1	81	0.1	0.22	0.83	4.43	1.022	5.5707
2	182	0.1	0.22	0.76	4.16	0.9461	4.7089
3	121	0.045	0.22	0.68	3.81	0.6721	3.7334
4	122	0.25	0.22	0.96	4.92	1.3070	6.6211
5	123	0.1	0.07	0.74	4.05	0.5851	3.5764
6	119	0.1	0.7	0.86	4.55	0.8574	4.7724
	Average deviation %					**7.13**	**7.97**

Deviation of surface roughness parameters of RSM and neural network models is on Figure 3, shown.

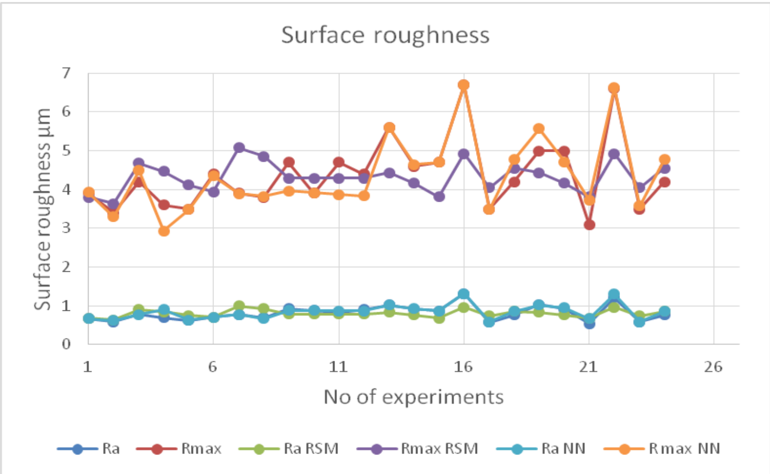

Figure 3 – Deviation of surface roughness parameters models

Any change in the cutting speed leads to a slowly corresponding change in the value of surface roughness. The cutting speed has a small and decreasing effect, Figure 5. Influence of feed on value surface roughness is higher than the cutting speed effect. Increasing feed increase surface roughness, Figure 6. Depth of cut at least influences the surface roughness values slightly, Fig 7.

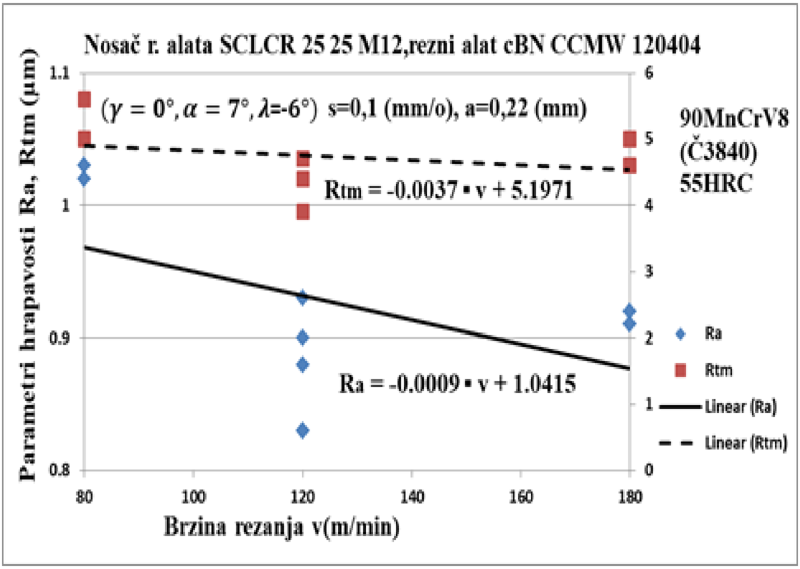

Figure 4 – The surface roughness (R_a, R_{max}) versus cutting speed

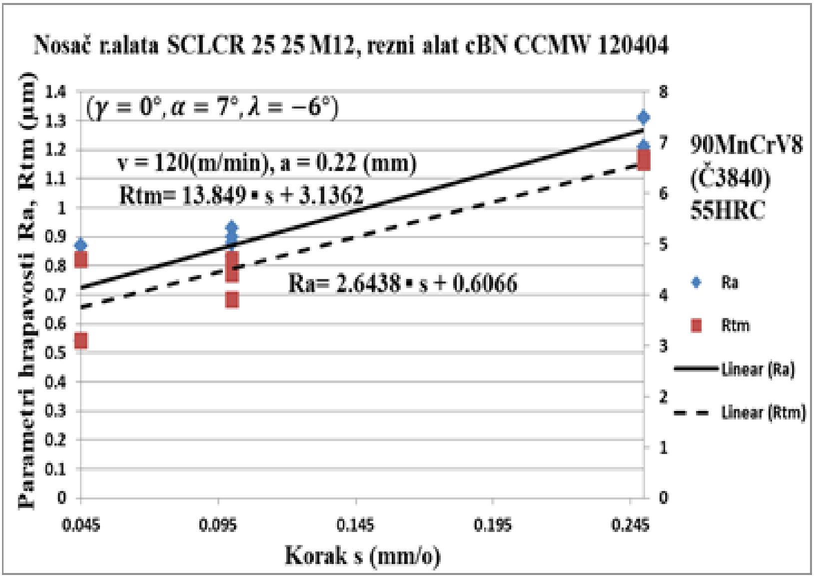

Figure 5 – The surface roughness (R_a, R_{max}) versus feed

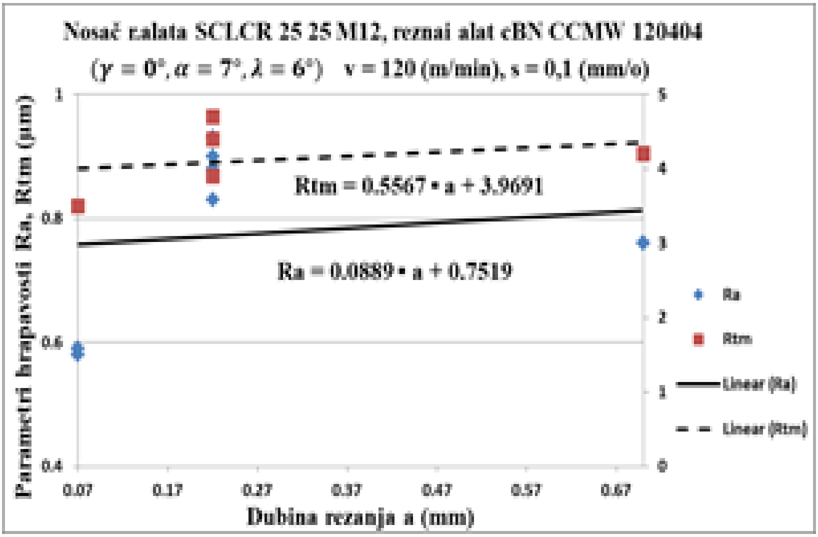

Figure 6 – The surface roughness (R_a, R_{max}) versus the cutting depth

Any change in the cutting speed leads to a slowly corresponding change in the value of surface roughness. The cutting speed has a small and decreasing effect, Figure 4. Influence of feed on value surface roughness is higher than the cutting speed effect. Increasing feed increase surface roughness, Figure 5. Depth of cut at least influences the wear on the flank surface and surface roughness values slightly.

4. Conclusion

Intelligent optimization techniques give the influence of cutting conditions on machining surface quality during turning hard material, are investigated through experimental verification. The investigation results confirm the highly consent of experimental research and intelligent techniques modeling. The intelligent optimization techniques and experimental results show some good information which could be used by future researches for optimal control of machining conditions. This paper has successfully established neural network model, for predicting the workpiece surface roughness parameters. Figures 4 and 5 shows the compared predicted values obtained by experiment and estimated by neural network shows a good comparison with those obtained experimentally. The average deviations of models are checked and are found to be adequate. The model adequacy can be further improved by considering more variables and ranges of parameters.

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