RSM and Neural Network Modeling of Surface Roughness During Turning Hard Steel

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Abstract. In the paper examined was the influence of the cutting regime parameters on surface roughness parameters during turning of hard steel with cubic boron nitrite cutting insert. In this study for modeling of surface finish parameters was used central compositional design of experiment and artificial neural network. The values of surface roughness parameters R_a and R_t 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 with central composition plan modeling technique and artificial neural network can be effectively used for the prediction of the surface roughness for hard steel and determined significand cutting regime parameters.

Keywords: RSM · Neural network · Surface roughness · Hard steel

1 Introduction

Increasingly, research in manufacturing processes and systems is evaluating processes to improve their efficiency, productivity and quality. The quality of finished products is defined by how closely the finished product adheres to certain specifications, including dimensions and surface quality. Surface quality is defined and identified by the combination of surface finish, surface texture, and surface roughness. Surface roughness (R_a, R_{max}) is the commonest index for determining surface quality [1, 2].

Manufacturing processes do not allow achieving the theoretical surface roughness due to defects appearing on machined surfaces and mainly generated by deficiencies and imbalances in the process. Due to these aspects, measuring procedures are necessary; as it permits one to establish the real state of surfaces to manufacture parts with higher accuracy. To know the surface quality, it is necessary to employ theoretical models making it feasible to do predictions in function of response parameters [3–5].

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A lot of analytically methods were also developed and used for predicting surface roughness. An empirical model for prediction of surface roughness in finish turning [6]. Nonlinear regression analysis, with logarithmic data transformation is applied in developing the empirical model. Metal cutting experiments and statistical tests demonstrate that the model developed in this research produces smaller errors and has a satisfactory result. The mathematical models for modeling and analyzing the vibration and surface roughness in the precision turning with a diamond cutting tool [7].

Recently, some initial investigations in applying the basic artificial intelligence approach to model of machining processes, have appeared in the literature, concludes that the modeling of surface roughness in machining processes has mainly used Artificial Neural Networks and fuzzy set theory [8, 9]. Average mean arithmetic surface roughness, Ra using artificial neural network was predicted in [10]. Surface roughness and surface finish have been considered in [11–14]. 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 [15]. 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 φ [16]. Use of coolants and lubricants in hard machining were presented in [17, 18].

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

2 Experimental Procedure and Material

Machining tests was done on the universal lathe - Prvomajska DK480. In the study was used interchangeable insert of CBN (cubic boron nitrite) CNMA 120404 ABC 25/F producer ATRON Germany. Used was appropriate insert holder for external processing PCLNR 25 25 M16.

The markings of the cutting tips according to DIN 4983 more closely define 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 (–6°) (Table 1).

Table 1. Experimental input factor levels

Factor levels	Cutting speed v (m/min)	Feed f (mm/rev)	Dept of cut a (mm)
Highest +1.41	180	0,25	0,7
High +1	160	0,2	0,5
Middle 0	120	0,1	0,22
Small –1	90	0,05	0,1
Smallest –1.41	80	0,045	0,07

The machining regime was:

- Cutting speed (m/min),
- Feed f (mm/rev), and
- depth of cut, a (mm).

Preparation of the workpiece was carried out before the experimental performance. The workpiece was thermally treated steel Č3840 (90MnCrV8) whose hardness after heat treatment was 55 HRC, cross-section 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. Cutting without the presence of cooling and lubricating agents was provided

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 Fig. 1.

Fig. 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.

Implementation of factorial experimental plan: in the Table 3 are given results of dispersion analyses, adequacy of models and significance of parameters.

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	0.61	3.7	0.39	2.86	0.6592	3.7574
2	160	0,05	0,10	0.36	2.1	0.38	2.80	0.3557	1.9229
3	90	0,20	0,10	0.81	4.5	0.88	4.81	0.8331	4.6422
4	160	0,20	0,10	0.62	3.46	0.86	4.71	0.5893	2.9841
5	90	0,05	0,50	0.71	5.1	0.39	2.59	0.7777	5.0833
6	160	0,05	0,50	0.47	4.8	0.38	2.54	0.6832	5.3483
7	90	0,20	0,50	0.8	4.2	0.89	4.36	0.8527	4.0420
8	160	0,20	0,50	0.73	4.1	0.87	4.26	0.8288	4.4420
9	120	0,10	0,22	0.53	2.8	0.58	3.50	0.3581	1.6534
10	120	0,10	0,22	0.48	2.9	0.58	3.50	0.3588	1.6588
11	120	0,10	0,22	0.33	1.8	0.58	3.50	0.3582	1.6539
12	120	0,10	0,22	0.34	1.8	0.58	3.50	0.3558	1.6365
13	80	0,10	0,22	0.42	2.2	0.59	3.55	0.2565	1.5225
14	180	0,10	0,22	0.66	3.1	0.57	3.45	0.59537	2.7949
15	120	0,045	0,22	0.27	2.1	0.36	2.59	0.3057	1.7402
16	120	0,25	0,22	1.80	8.1	1.00	4.93	1.8051	8.2975
17	120	0,10	0,07	0.60	6.6	0.58	3.75	0.7843	6.6161
18	120	0,10	0,70	0.70	3.9	0.59	3.26	0.7456	3.9992
19	80	0,10	0,22	0.47	2.9	0.59	3.55	0.4533	2.5444
20	180	0,10	0,22	0.652	3.48	0.57	3.45	0.6655	3.2542
21	120	0,045	0,22	0.33	2.15	0.36	2.59	0.2790	1.8978
22	120	0,25	0,22	1.9	8.2	1.00	4.93	1.8304	8.3473
23	120	0,10	0,07	0.73	6.2	0.58	3.75	0.8895	6.6167
24	120	0,10	0,70	0.445	2.48	0.59	3.26	0.5301	2.2659

Table 3. Adequacy of models and significance of parameters

Model adequacy		R_a	R_{max}
		Fa = 3,2288	Fa = 4,0491
Significance of parameters	F_{ro}	143,19	655,65
	Fr1 (v)	0,05 (*)	0,03 (*)
	Fr2 (f)	53,95	18,75
	Fr3 (a)	0,01(*)	0,682 (*)

Analyze of adequacy of models shows that both models are adequate because coefficients are smaller than $F_t = 6.61$. Cutting speed and depth of cut are not significant because values are smaller than $F_t = 4.47$.

2.1 Artificial Neural Network Modelling

Artificial neural network (ANN) 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 [14]. 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, [mm] the depth of cut. The outputs are the values of surface roughness parameters: arithmetic mean roughness R_a and maximal roughness hight R_{max}. These parameters were set to optimize by the neural network performance: 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.

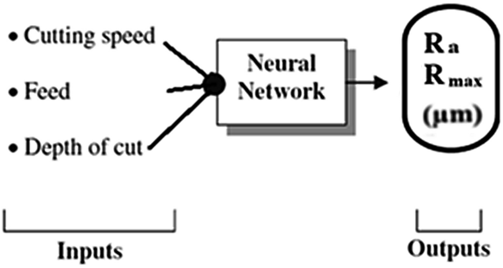

Fig. 2. Network input and output layer

3 Results and Discussions

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

$$R_a = 2,8264 \cdot v^{-0,04471} \cdot s^{0,58975} \cdot a^{0,00716}$$

$$R_{max} = 9,0036 \cdot v^{-0,3717} \cdot s^{0,37380} \cdot a^{-0,6148}$$

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 4, side by side with the obtained experimental results. For reduction of a deviation, is needed to increase the number of inputs.

Table 4. Experimental values and values obtained by neural network with percentage deviation for 6 testing points

No.	Factor			R_i – experimental 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	0.47	2.9	0.4533	2.5444
2	182	0.1	0.22	0.652	3.48	0.6655	3.2542
3	121	0.045	0.22	0.33	2.15	0.2790	1.8978
4	122	0.25	0.22	1.9	8.2	1.8304	8.3473
5	123	0.1	0.07	0.73	6.2	0.8895	6.6167
6	119	0.1	0.7	0.445	2.48	0.5301	2.2659
	Average deviation %					**10.30**	**8.62**

Calculation of percental deviation 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 is 8.94 and for R_{max} is 9.94. Experimental values and values obtained by neural network with percentage deviation for 6 testing points for neural network are in Table 4.

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, Fig. 3. Influence of feed on value surface roughness is higher than the cutting speed effect.

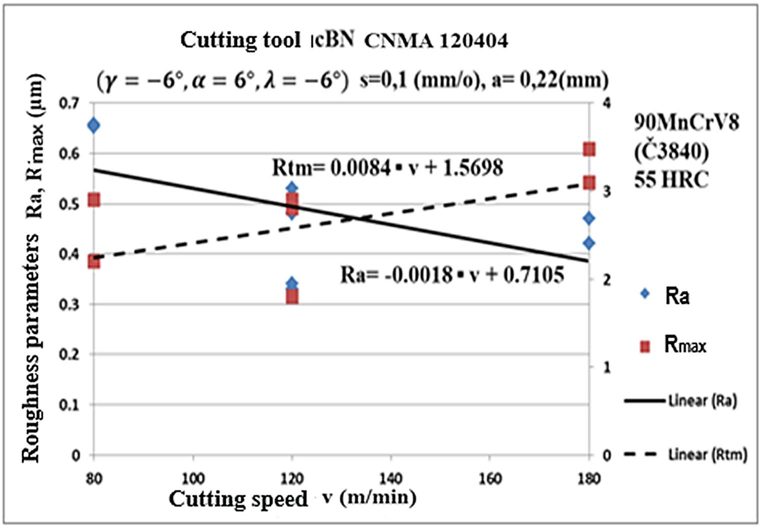

Fig. 3. The surface roughness (R_a, R_{max}) versus cutting speed

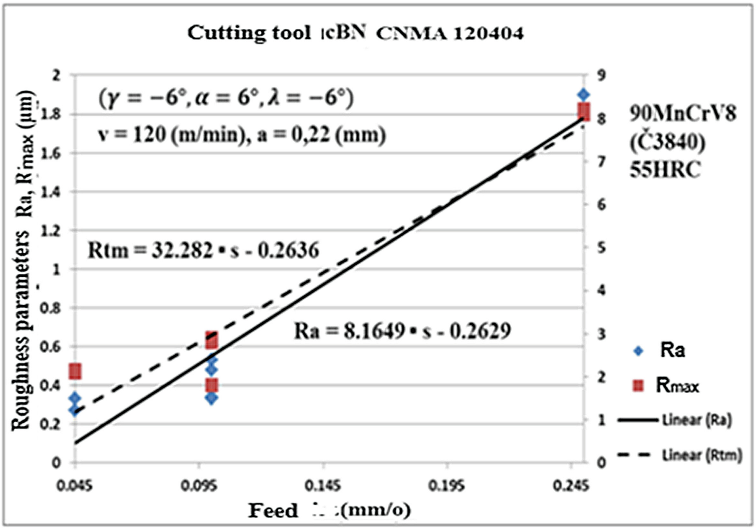

Fig. 4. The surface roughness (R_a, R_{max}) versus feed

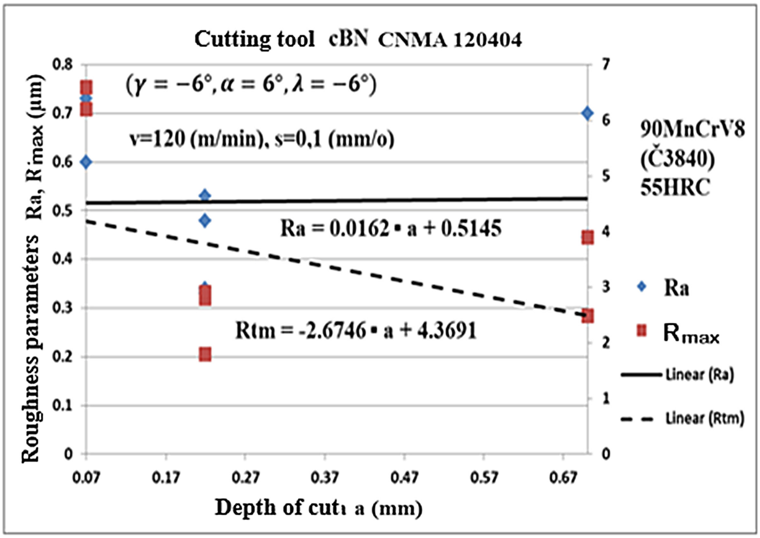

Fig. 5. The surface roughness (R_a, R_{max}) versus the cutting depth

Increasing feed increase surface roughness, Fig. 4. Depth of cut at least influences the wear on the flank surface and surface roughness values slightly, Fig. 5.

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, Fig. 4. Influence of feed on value surface roughness is higher than the cutting speed effect. Increasing feed increase surface roughness, Fig. 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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References

1. Chen JC, Savage M (2001) A fuzzy-net-based multilevel in-process surface roughness recognition system in milling operations. Int J Adv Manuf Technol 17:670–676
2. Quintana G, Garcia-Romeu ML, Ciurana J (2009) Surface roughness monitoring application based on artificial neural networks for ball-end milling operations. J Intell Manuf 22: 607–617
3. Sivarao IR, Castillo WJG, Taufik (2000) Machining quality predictions: comparative analysis of neural network and fuzzy logic. Int J Electr Comput Sci IJECS 9:451–456
4. Drégelyi-Kiss Á, Horváth R, Mikó B (2013) Design of experiments (DOE) in investigation of cutting technologies. In: Development in machining technology (DIM 2013), Cracow, pp 20–34
5. Maňková I, Vrabeľ M, Beňo J, Kovač P, Gostimirovic M (2013) Application of Taguchi method and surface response methodology to evaluate of mathematical models for chip deformation when drilling with coated and uncoated twist drills. Manuf Technol 13(4): 492–499
6. Hadi SG, Ahmed SG (2006) Assessment of surface roughness model for turning process. In: Knowledge enterprise: intelligent strategies in product design, manufacturing, and management. International federation for information processing (IFIP), vol 207, pp 152–158
7. Chen CC, Chiang KT, Chou CC, Liao YC (2011) The use of D-optimal design for modeling and analyzing the vibration and surface roughness in the precision turning with a diamond cutting tool. Int J Adv Manuf Technol 54:465–478
8. Choudhary A, Harding J, Tiwari M (2009) Data mining in manufacturing: a review based on the kind of knowledge. J Intell Manuf 20(5):501–521
9. Grzenda M, Bustillo A, Zawistowski P (2012) A soft computing system using intelligent imputation strategies for roughness prediction in deep drilling. J Intell Manuf 23:1733–1743
10. Balic J, Korosec M (2002) Intelligent tool path generation for milling of free surfaces using neural networks. Int J Mach Tools Manuf 42:1171–1179
11. Pérez CJL (2002) Surface roughness modeling considering uncertainty in measurements. Int J Prod Res 40(10):2245–2268
12. Azouzi R, Gullot M (1997) On-line prediction of surface finish and dimensional deviation in turning using neural network-based sensor fusion. Int J Mach Tools Manuf 37(9):1201–1217
13. Ho SY, Lee KC, Chen SS, Ho SJ (2002) Accurate modeling and prediction of surface roughness by computer vision in turning operations using an adaptive neuro-fuzzy inference system. Int J Mach Tools Manuf 42(13):1441–1446
14. Zębala W, Gawlik J, Matras A, Struzikiewicz G, Ślusarczyk Ł (2014) Research of surface finish during titanium alloy turning. Key Eng Mater 581:409–414
15. Rajasekaran T, Palanikumar K, Vinayagam BK (2011) Application of fuzzy logic for modeling surface roughness in turning CFRP composites using CBN tool. Prod Process 5 (2):191–199

16. Savković B, Kovač P, Gerić K, Sekulić M, Rokosz K (2013) Application of neural network for determination of cutting force changes versus instantaneous angle in face milling. J Prod Eng 16(2):25–28
17. Kundrák J, Varga G (2013) Use of coolants and lubricants in hard machining. Tech Gaz 20 (6):1081–1086
18. Kovac P, Rodic D, Pucovsky V, Savkovic B, Gostimirovic M (2013) Application of fuzzy logic and regression analysis for modeling surface roughness in face milling. J Intell Manuf 24(4):755–762