D. BAJIĆ, B. LELA, D. ŽIVKOVIĆ

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MODELING OF MACHINED SURFACE ROUGHNESS AND **OPTIMIZATION OF CUTTING PARAMETERS IN FACE MILLING**

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The influence of cutting parameters on surface roughness in face milling has been examined. Cutting speed, feed rate and depth of cut have been taken into consideration as the influential factors. A series of experiments have been carried out in accordance with a design of experiment (DOE). In order to obtain mathematical models that are able to predict surface roughness two different modeling approaches, namely regression analysis and neural networks, have been applied to experimentally determined data. Obtained results have been compared and neural network model gives better explanation of the observed physical system. Optimal cutting parameters have been found using simplex optimization algorithm.

Key words: face milling, surface roughness, Regression, Neural networks

Modeliranje hrapavosti obrađene površine i optimiranje parametara obrade pri čeonom glodanju. U ovom radu istražen je utjecaj parametara obrade (brzina rezanja, posmak i dubina rezanja) na hrapavost obrađene površine pri čeonom glodanju. Obavljen je niz pokusa u skladu sa planom eksperimenta. U cilju dobivanja matematičkog modela kojim se može predvidjeti hrapavost obrađene površine, eksperimentalni podaci obrađeni su metodologijom regresijske analize i neuronskih mreža. Uspoređeni su dobiveni rezultati i neuronska mreža daje bolji opis promatranog fizikalnog sustava. Primjenom simplex algoritma za optimiranje dobivene su optimalne vrijednosti ispitivanih parametara.

Ključne riječi: čeono glodanje, hrapavost obrađene površine, regresijska analiza, neuronske mreže

INTRODUCTION

The surface quality is one of the most specified customer requirements and the major indicator of surface quality on machined parts is surface roughness. The surface roughness is mainly a result of various controllable or uncontrollable process parameters and it is harder to attain and track than physical dimensions are. A considerable number of studies have researched the effects of the cutting speed, feed, depth of cut, nose radius and other factors on the surface roughness. In recent studies [1, 2, 3] the effects of some factors on surface roughness has been evaluated and models has been developed. A central task in science and engineering practice is to develop models that give a satisfactory description of physical systems being observed. The goal of this study is to obtain a mathematical model that relates the surface roughness to three cutting parameters in face milling, precisely to the cutting speed, feed rate and depth of cut. In this work two different approaches have been used in order to get the mathematical models. The first approach is a design of experiment (DOE) together with an analysis of variance (ANOVA) and regression analysis (RA). The second approach is modeling by means of artificial neural networks (ANNs).

SURFACE ROUGHNESS

The surface parameter used to evaluate surface roughness in this study is the roughness average (Ra).

The roughness average is the area between the roughness profile and its central line, or the integral of the absolute value of the roughness profile height over the evaluation length.

There are a great number of factors influencing the surface roughness and Figure 1 shows all influential factors on machined surface roughness.

CONDITIONS OF EXPERIMENT

Test samples made of carbon steel St 52-3 with dimensions 230x100x100 mm were prepared and used in experiments. The face milling experiments were performed by a tool for the face milling Helido 45°, S845 F45SX D063-05-22-R16 using inserts with 8 helical right-hand cutting edges, produced by Iscar.

D. Bajić, B. Lela, D. Živković, Faculty of Electrical Engineering, Mechanical Engineering and Naval Architecture, University of Split, Split, Croatia

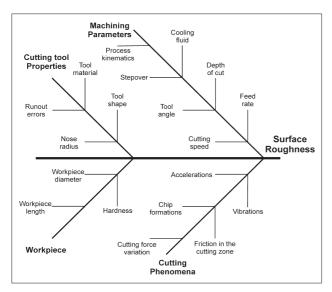


Figure 1. Fishbone diagram with factors that influence on surface roughness [4]

The type of a machine used for the milling test was machining center VC 560 manufactured by Spinner. The surface roughness values of finish-milled workpieces were measured by Surtronic 3+ instrument, produced by Rank Taylor Hobson. The measurements were repeated ten times. During the process of measuring, the cutoff length was taken 0,8 mm and the sampling length 5,6 mm. Altogether 36 experiments were conducted. Twenty experiments were conducted in order to allow performing ANOVA and RA, and additional 16 experiments to obtain additional data for neural network training and verification of modeling.

DESIGN OF EXPERIMENT

In this research the design of experiment was realized using the rotatable central composite design (RCCD). The aim of this work is to find mathematical models that describe the dependence of machined surface roughness on three cutting parameters:

- the cutting speed, v_c ,

- the feed rate, f,
- the depth of cut, a_p .

The RCCD models the response using the empirical second-order polynomial and demands altogether 20 experiments, 8 experiments on the vertices of a cube (3 factors on two levels, 2^3), 6 experiments on the central axes and 6 repeated experiments on the average level.

Through the regression analysis of the experimental results, using software Design Expert 6.0, the values of the model coefficients have been obtained and the regression equation is:

$$Ra = -5.947 + 0.08 \cdot v_c + 7.934 \cdot f + 1876 \cdot a_p \qquad (1)$$

$$-0.0003 \cdot v_c^2 + 15801 \cdot f^2 - 0.111 \cdot a_p^2$$

$$-0.067 \cdot v_c \cdot f - 0.006 \cdot v_c \cdot a_p - 2.859 \cdot f \cdot a_p$$

NEURAL NETWORK MODEL

This research uses Bayesian neural network (BNN) modeling approach. BNN gives probabilistic interpretation to the network learning process [5] and automatically control the network complexity so there is no need for validation data set and cross-validation procedure. The BNN model used in this work consists of three layers with 3, 5 and 1 neurons in the input, hidden and output layer, respectively. The output layer has linear activation function. In order to optimize BNN weights, the scaled conjugate gradient algorithm [5] was used. The final values of the hyperparameters are $\alpha = 2,88$ and $\beta = 20,39$. Out of 36 experiments 29 data pairs were chosen for the procedure of training and testing of BNN model. Furthermore 9 data pairs were randomly selected so as to form the testing data set. The remained 20 data pairs were used in the training process.

The effectiveness of training of the BNN model and its ability to predict correct values for unseen data can be given in a form of regression analysis where correlation coefficient R determines the correspondence between the BNN outputs and targets. The R-value of 0,948 and 0,940 were obtained for the training and testing of BNN model, respectively. These values indicate that the model has been very well learnt and that also has the excellent generalization ability.

ANALYSIS OF RESULTS

Validation of both models was performed with the testing data set that had not been used in the training process. Relative error, obtained using both RA and BNN methodologies, have been compared in order to determine the capability of accurate predictions of the surface roughness. Results of testing are shown in Table 1. Results from Table 1 indicate that the BNN model offers better prediction capability. The results obtained from

 Table 1.
 Testing the capability of both models for predictions of the surface roughness

v _c / m/min	<i>f</i> / mm/t	a _p / mm	Experiment	⊈ Ra / μm	BNN	Relative error obtained by RA / %	Relative error obtained by BNN / %
			ιτα / μπ				
108	0,35	1,4	1,67	1,47	1,61	11,72	3,75
80	0,36	2,7	1,82	1,69	1,92	7,23	5,40
110	0,28	2,2	1,14	1,00	1,09	12,59	4,59
90	0,35	1,4	1,8	1,68	1,79	6,84	0,62
100	0,33	1,7	1,25	1,43	1,49	14,03	18,99
95	0,20	2	0,97	0,91	0,93	5,80	4,05
85	0,33	2,6	1,68	1,49	1,61	11,12	4,40
105	0,38	1,5	1,73	1,76	1,94	1,63	12,01
86	0,34	1,1	1,7	1,57	1,74	7,55	2,46

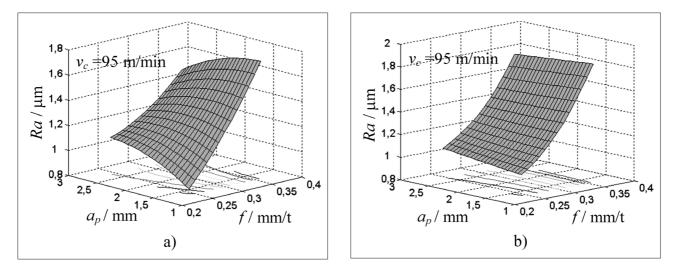


Figure 2. Influence of depth of cut and feed on surface roughness at constant cutting speed $v_c=95$ / m/min: a-results from the regression model; b-results from BNN model

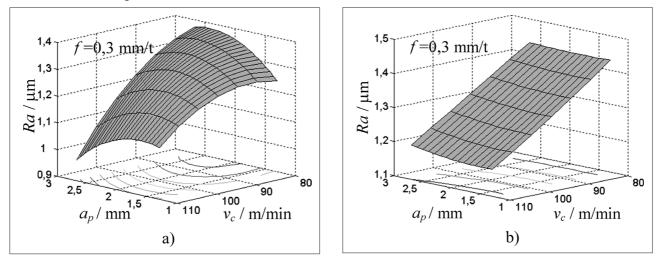


Figure 3. Influence of cutting speed and depth of cut on surface roughness at constant feed f=0,3 / mm/t: a-results from the regression model; b-results from BNN model

both models in a form of graphical representation are depicted on Figures 2, 3 and 4.

Figure 2 shows the response surfaces for *Ra* for both RA (Figure 2.a) and BNN (Figure 2.b) modeling methodology for the case when the feed and depth of cut are variables and the cutting speed is constant 95 m/min. It is obvious that the feed appears as a dominant influential factor on *Ra*. The depth of cut has a minor influence on the surface roughness.

On Figure 3 can be seen functional dependence of Ra on the cutting speed and depth of cut for the invariable feed value of 0,3 mm/t. Responses from RA and BNN model are shown on Figure 3.a and Figure 3.b, respectively. It can be seen that the dominant factor influencing the surface roughness is the cutting speed and the depth of cut shows negligible influence.

Figure 4 shows the influence of the feed and cutting speed on the roughness at the constant depth of 2 mm. Figure 4.a shows predictions for the regression model and Figure 4.b for the BNN model. Obviously, both factors v_c and f influence on Ra but the feed is again the more influential cutting parameter.

In order to get optimal cutting parameters that give the minimal value of the surface roughness, the optimization using simplex optimization algorithm was conducted. The optimization was performed on the BNN model due to its better prediction ability. The minimum value of $Ra=0.81 \mu m$ would be obtained if the studied cutting parameters were set as follows: $v_c=110 m/min$, f=0.19 mm/t and $a_p=0.82 mm$.

CONCLUSIONS

The influences of the cutting speed, depth of cut and feed on machined surface roughness in face milling process have been examined. Experiments have been performed on steel St 52-3 and the obtained data has been analyzed using both RA and BNN modeling approach.

Both methodologies are capable for accurate predictions of the surface roughness, although BNN model gives somewhat better predictions, with the approximately relative error of 6,3 %. The same size of the data set (20 data pairs) was used for inferring the parameters

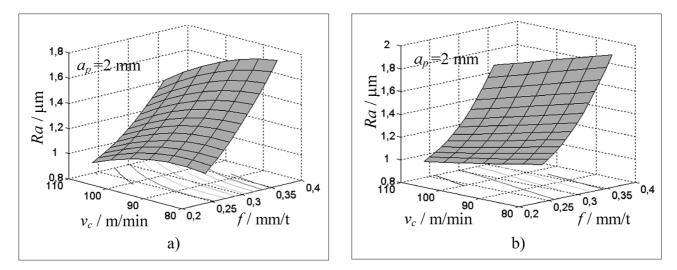


Figure 4. Influence of cutting speed and feed on surface roughness at constant depth $a_p=2$ mm: a- results from the regression model; b-results from BNN model

of both models. So BNN model with the training data set that small can give even better predictions than the regression model.

The results of the performed research show that both feed and cutting speed influence on surface roughness but the feed is the most influential factor. The depth of cut has a negligible influence on the surface roughness. The minimum surface roughness can be achieved by setting the feed as low as possible and the cutting speed as high as possible.

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Note: The responsible translator is the Author D. Bajić