Comparative Analysis of Surface Quality Prediction Models

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Abstract **- The paper presents a comparative analysis of the models for predicting machined surface quality developed by the application of multiple regression and artificial neural networks. The models were developed using experimental data for the mean arithmetic deviation of surface roughness and the axial cutting force obtained by implementing the Taguchi experiment plan. Comparative analysis of the models has shown that artificial neural networks give the best results in terms of predicting the mean arithmetic deviation of surface roughness on the basis of process parameters and axial cutting force.**

Keyword - models, axial force, prediction, surface roughness

I. INTRODUCTION

Experimental research seeks to establish dependence between quality of the machined surface and parameters of the cutting process. Prediction of the machined surface quality through the mean arithmetic deviation of the surface roughness (R_a) is made by using a multiple regression mathematical model and by applying models based on artificial neural networks that connect machining process input parameters with the quality of the machined surface.

Çiçek, Kivak and Samtaş [1], using the Taguchi experiment design in a drilling operation on austenitic stainless steel AISI 316 with high-speed steel (HSS) twist drills, conventionally and cryogenic, varying feed f *(mm/o)* and the cutting speed v_c *(m/min)* at two levels, develop a regression model that combines the indicated parameters with the machined surface quality through the mean arithmetic deviation R_a *(μm)*, with a 96,3% coefficient of determination.

Rodrigues et al. [2] use a regression analysis to obtain a mathematical model that links the spindle speed n *(rpm)*, feed f *(mm/rev)* and cutting depth a *(mm)* with the machined surface quality through the mean arithmetic deviation R_a *(μm)* by conducting a full experiment plan and varying of the mentioned parameters at three levels in a turning operation on structural steel with high-speed steel (HSS) tools. The adjusted coefficient of determination in this case is 66,1% which indicates a strong connection between the machined surface quality and the mentioned parameters.

Raghunandan, Bhandarkar and Pankaj [3], based on the data obtained using the Taguchi experiment design in a truning operation on EN-19 material with cemented carbide inserts, come up with a model linking a mean arithmetic deviation of surface roughness R_a *(μm)*, cutting speed v_c *(m/min)*, feed f *(mm/rev)* and cutting depth a *(mm)*. The adjusted coefficient of determination, which describes the given connection, in this case is 52,8%.

Ficici, Koksal and Karacadag [4] investigate the effect of tool modification (twist drill cutting edge grinding in *μm*), cutting speed v_c *(m/min)* and feed f *(mm/rev)*, using Taguchi experiment design in a drilling operation on austenitic stainless steel AISI 304 with high-speed steel (HSS) twist drills. Development of the regression model links the stated parameters with the machined surface quality through the mean arithmetic deviation R_a *(μm)* and the implementation of the confirmatory experiment using the optimal combination of parameters find that the prediction error is 4,34%.

Rashid and Lani [5], in addition to using multiple regression to obtain a mathematical model, use artificial neural networks for predicting surface roughness in a milling operation on aluminum. By performing the experiment, using a complete factorial plan, they develop the models that connect surface roughness expressed through the mean arithmetic deviation of the roughness profile R_a *(μm)*, the spindle speed n *(rpm)*, the velocity of the auxiliary motion v_f *(mm/min)* and depth of cut a *(mm)*. The developed mathematical model gives the result with an average error of 13,3%, while the artificial neural network shows more favorable results with 6,42% of the average error.

Šimunović, Šarić and Lujić [6] apply artificial neural networks for predicting the surface roughness of a workpiece of steel Č.4730 (EN 25CrMo4), machined by turning, using as input parameters the type of material, type of tool, depth of cut, feed and spindle speed. This model, based on artificial neural networks, gives results with an average error of less than 5% in the light of the data used to train, validate and test the possibilities of the model.

Konanki and Sadineni [7], by conducting the Taguchi experiment plan and using input data for the cutting speed v_c *(m/min)*, spindle speed *n (rpm)* and depth of cut *a (mm)* varied on three levels in a turning operation on AA 6351 alloy, develop a model for predicting surface roughness on the basis of artificial neural networks using a mean arithmetic deviation R_a *(µm)* with an average test error of 2,24%.

These models give a good approximation of the experimental results, but do not take into account the impact of the tool wear on the quality of the machined surface.

Nedić, Tadić and Đorđević [8], on the basis of experimental investigationsin turning and drilling operations on softly annealed steels with pearlite-ferrite structure, come to a polynomial dependence in the form of a third-degree polynom between the mean arithmetic deviation of the surface roughness R_a *(µm)* and machining tools wear *VB (mm)*.

Spaić and Marinović [9], by using the artificial neural networks based on the experimental results obtained in a drilling operation on steel Č.4732 (EN 42CrMo4) with high-speed steel twist drills, establish a model for the axial drilling force F_3 *(N)* dependent on the tool wear width *VB (mm)*. They demonstrate that artificial neural networks can be adequately used to predict the axial drilling force as a carrier of information on the tool wearing.

Xu, Hiroyuki and Wei [10] show that tool wear *VB (mm)* in a drilling operation on aluminum alloys can be predicted by means of artificial neural networks by using process input parameters such as depth of cut *a (mm)*, spindle speed *n (rpm)* and feed *f (mm/rev)*, adding the values of measurable process parameters such as axial cutting force F_3 *(N)* and torque *M (Nm)*.

Considering the aforesaid, it appears possible to develop multiple regression models and a model based on the application of artificial neural networks that will include both the process input parameters (the speed, the feed, the depth of cut) and measurable machining process parameters associated with machining tools wear (the force, the torque etc.) at the same time enabling a comparative analysis and reaching a conclusion on the character of the error of individual models.

II. MULTIPLE REGRESSION MODELS

A multiple regression model successfully describes interdependence of the phenomena in reality, and the aim of multiple regression is to make predictions of dependent variable variations based on the estimated model for different combinations of explanatory variables values [11].

Multiple linear regression model which is applied in cases when there are several explanatory (independent or regression) variables can be written in the form:

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + ... + \beta_k x_k + e .$$

In this model, the variable y is the dependent variable, $x_1, x_2, ... , x_k$ are independent variables, $\beta_0, \beta_1, \beta_2, ... , \beta_k$ are the regression coefficients (the parameters of the model to be determined), and e is a random variable.

Given a statistical (random) sample of size n to be used for establishing the relationship between dependent variable y and the independent variables x_1, x_2, ... , x_k, the following n equation corresponds to the above equation:

$$y_i = \beta_0 + \beta_1 x_{1i} + \beta_2 x_{2i} + ... + \beta_k x_{ki} + e_i, \quad i = 1,....n .$$

The basic task of forming the regression model is reduced to the estimate of unknown parameters of the model $\beta_0, \beta_1, \beta_2, ... , \beta_k$, to obtaining the estimated values of the parameters $b_0, b_1, b_2, ... , b_k$ by the least squares method, and to forming the model as follows:

$$\hat{y} = b_0 + b_1 x_1 + b_2 x_2 + ... + b_k x_k .$$

To determine the model adaptation to empirical data, a standard error of regression and a coefficient of determination is used where the standard error of regression s represents the estimate of the random error σ standard deviation, while the coefficient of determination R^2 shows the percentage of dependent variable variations explained by the combined impact of the explanatory variables included in the model [11].

The standard error of regression s, as the absolute measure of representativity expressed in the units of dependent variable y, is determined as the square root of the estimated value of the random error $\hat{\sigma}^2$ variance and the number of degrees of freedom n-(k+1):

$$s = \sqrt{\hat{\sigma}^2} = \sqrt{\frac{\sum_{i=1}^{n} e_i^2}{n-(k+1)}}, \; (e_i = \hat{y}_i - y_i).$$

The coefficient of determination R^2, as the relative measure of representativity of the model obtained, is a quantitative measure of the linear dependence degree of the dependent variable y and several independent variables $x_1, x_2, \ldots, x_k$, and is determined as the ratio of regression variance and total variance [12]:

$$R^2 = \frac{\sum_{i=1}^{n} (\hat{y}_i - \bar{y})^2}{\sum_{i=1}^{n} (y_i - \bar{y})^2}.$$

When the number of data in a random sample is small and several independent variables $x_1, x_2, \ldots, x_k$, are observed, the coefficient of determination is high thus requiring its correction by taking into account the number of variables and the sample size n. This is done using the adjusted coefficient of determination $\bar{R}^2$, defined as [11]:

$$\bar{R}^2 = 1 - \frac{n-1}{n-(k+1)}(1-R^2).$$

The adjusted coefficient of determination $\bar{R}^2$, which is always less than the coefficient of determination of R^2 whose value approaches the value of the coefficient of determination by increasing the number of data in the sample, in this case represents a more precise relative measure of the model's representativeness.

In addition to determining the standard error of regressions s and the coefficient of determination R^2, determination of the sense of the dependent variable y estimation based on each of the independent variable x_1, $x_2, \ldots, x_k$ requires significance testing of the estimated parameters $b_0, b_1, b_2, \ldots, b_k$ [13].

The precondition for testing significance of the parameters is to calculate the standard error of a parameter S_{b_j}, $j = 1,\ldots,k$:

$$S_{b_j} = \sqrt{\frac{s^2}{\sum x_{ji}^2 - n\bar{x}_j^2}}.$$

The statistical significance of the estimated regression parameters is determined on the basis of the limit table t-value and the calculated value t_j:

$$t_j = \frac{b_j}{S_{b_j}}.$$

By reading the limit values from the t-tables for degree of freedom n-(k+1) and significance level p one can draw a conclusion on the statistical significance of the evaluated parameters and the sense for estimation of the dependent variable y on the basis of an independent variable x_j. In case of $|t_j| < t$ the estimate of the dependent variable y makes sense.

A multiple nonlinear regression model which is applied in cases when there are several independent variables can be written in the form:

$$y = \beta_0 \cdot x_1^{\beta_1} \cdot x_2^{\beta_2} \cdot \ldots \cdot x_k^{\beta_k} \cdot e.$$

A nonlinear regression model is reduced by the logarithmic transformation to the linear regression model of the form:

$$\log y = \log \beta_0 + \beta_1 \log x_1 + \beta_2 \log x_2 + \ldots + \beta_k \log x_k + \log e.$$

In the given model, the variable log y represents the dependent variable, and the log x_1, log x_2, ... , log x_k are independent variables.

Given a random sample of size n to be used for establishing relationship between the dependent variable y and the independent variables $x_1, x_2, \ldots, x_k$, the following n equation corresponds to the above equation:

$$\log y_i = \log \beta_0 + \beta_1 \log x_{1i} + \beta_2 \log x_{2i} + \ldots + \beta_k \log x_{ki} + \log e_i, \; i = 1,\ldots,n.$$

The basic task of forming the regression model in this case is reduced to the estimation of unknown parameters log β_0, β_1, β_2, ... , β_k, to obtaining the estimated values of the parameters log b_0, b_1, b_2, ... , b_k, and to forming the model in the form:

$$log\,\hat{y} = log\,b_0 + b_1\,log\,x_1 + b_2\,log\,x_2 + ... + b_k\,log\,x_k\,.$$

Determination of model adaptation to empirical data is also performed using the standard error of regression and the coefficient of determination. In order to determine the sense of the dependent variable log y estimation on the basis of each of the independent variables log x_1, log x_2, ... , log x_k significance testing of estimated parameters log b_0, b_1, b_2, ... , b_k is required.

Transformation of the obtained linear regression model leads to the formation of a nonlinear regression model which is formed to describe behavior of the dependent variable y:

$$\hat{y} = b_0 \cdot x_1^{b_1} \cdot x_2^{b_2} \cdot ... \cdot x_k^{b_k}\,.$$

III. Artificial Neural Networks Model

A model based on artificial neural networks consists of interconnected artificial neurons (Fig. 1) that imitate functioning of biological neurons. The signals x_1, x_2, ..., x_k, which are described by numerical quantities and multiplied by the weighting coefficients w_1, w_2, ... ,w_k, when entering the neuron are summed up analogously to the sum of the potential in the biological neuron body. If the summed number (weighting sum) is above the defined threshold w_{k+1}, the neuron produces the output signal y. Apart from the threshold, an artificial neuron can have an additional function, the transfer function f [14].

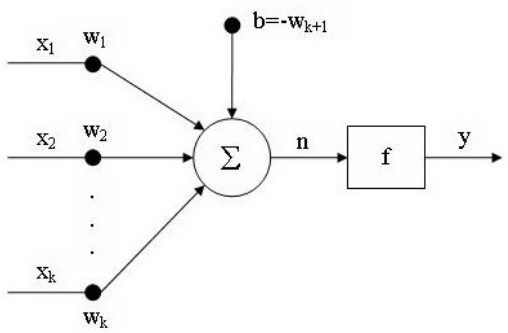

Fig. 1. Artificial neuron

The weighting sum, by adding an input signal x_{k+1} with a fixed value of 1, can be written in the form:

$$n = w_1x_1 + w_2x_2 + ... + w_kx_k - w_{k+1} \cdot x_{k+1} = \sum_{i=1}^{k} w_ix_i + b\,,$$

while the output y as the result of the transfer function f can be written in the form:

$$y = f(n) = f\left(\sum_{i=1}^{k} w_ix_i + b\right).$$

A rather common case seen in practice of establishing a connection between one dependent variable and multiple independent variables requires formation of a model based on artificial neural networks with multiple inputs, a single output, or an output layer, and one or more hidden layers (Fig. 2).

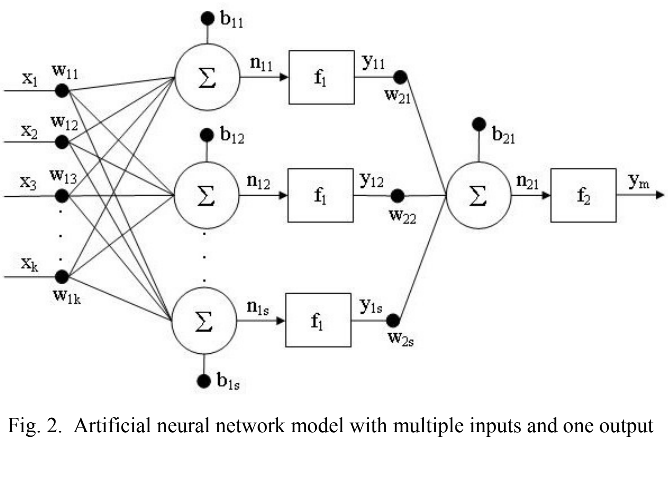

Fig. 2. Artificial neural network model with multiple inputs and one output

The transfer function can be a linear or non-linear function, and most commonly used transfer functions are linear, jump function and sigmoid transfer function [15].

In order for the neural network to represent non-linear relations, which in practice are most commonly used, it is necessary for the transfer function of its process elements, artificial neurons, to be a nonlinear function of its inputs. The function that fulfills this condition is a sigmoid transfer function [14].

Artificial neural networks require training, i.e. application of algorithms that adjust the amounts of weighting coefficients whereby a very popular Backpropagation learning algorithm for multilayer artificial neural networks, developed in the MATLAB software package, is used.

IV. Experiment Design

In this paper the Taguchi orthogonal experiment plan L_9 [16], given in Table I, with nine combinations of machining process parameters, was used.

TABLE I. Ortogonal Matrix L_9

Com. No.	Factors			
	X_1	X_2	X_3	X_4
1.	1	1	1	1
2.	1	2	2	2
3.	1	3	3	3
4.	2	1	2	3
5.	2	2	3	1
6.	2	3	1	2
7.	3	1	3	2
8.	3	2	1	3
9.	3	3	2	1

The experiment was conducted using twist drills (TD) DIN 338 Ø3, DIN 338 Ø5 and DIN 338 Ø8 made of high-speed steel Č.7680 (EN HS6-5-2) the chemical composition of which is given in Table II. The drills were produced by grinding technology and thermally machined to 64-68 HRC hardness, in black versions with normal blade (NB), manufactured by „Swisslion Industrija Alata, a.d.Trebinje".

TABLE II. Chemical Composition of Steel Č.7680 (EN HS6-5-2) [%]

C	W	Mo	Cr	V	Si	Mn	P	S
0,82-0,9	5,5-6,75	4,5-5,5	3,8-4,4	1,75-2,2	0,2-0,45	0,15-0,4	≤0,03	≤0,03

The input parameters of the drilling operation were the nominal diameter of the twist drill (*d*), speed (*n*), the feed (*f*), and the angle of installation of the workpiece (*ε*) was taken as an additional parameter.

Variation of the speed and feed was adopted based on the recommendation of the twist drills manufacturer. The adopted values of the experiment factors, the nominal diameter, the speed, the feed and the angle of installation of the test tube are given in Table III.

TABLE III. Experiment Factors Values

No.	d (mm)	n (o/min)	f (mm/rev)	ε (^{o})
1.	3	300	0,03	0
2.	5	500	0,05	3
3.	8	800	0,10	5

Material used in experiment for the test tubes was enhancement steel Č.4732 (EN 42CrMo4) thermally treated to 28 HRC hardness with chemical composition given in Table IV.

TABLE IV. Chemical Composition of Steel Č.4732 (EN 42CrMo4) [%]

C	Si	Mn	P	S	Cr	Mo
0,38-0,45	0,15-0,4	0,5-0,8	≤0,035	≤0,035	0,9-1,2	0,15-0,3

The dimensions of the test tubes determined on the basis of the planned drilling depth of l = 3d are given in Table V.

TABLE V. Dimensions of the Test Tubes

Twist drill	l (mm)	Test tube diameter (mm)	Test tube thickness (mm)
DIN 338 Ø 3,00	9	Ø 60	15
DIN 338 Ø 5,00	15		20
DIN 338 Ø 8,00	24		30

The experiment was conducted on the EMCO MILL 250 milling machine with the possibility of achieving a maximum speed of the main spindle of 10 000 *rpm* with the axis velocity range of 0-10 *m/min*, the possibility of achieving a maximum torque of 41 *Nm*, and EMCO WinNC numerical control with SIEMENS Sinumerik 810/840D software.

To determine the size of the twist drill flank wear an optical device GÜHRING PG 100 was used for measuring the geometric elements of twist drills with the possibility of digital reading of the measured values.

Measurement of the axial drilling force during the operation was conducted by KISTLER measuring chain for measuring axial force and torque with a measuring range up to 20 *kN*.

The mean arithmetic deviation values of the machined surface roughness profile was determined by using the measuring instrument SURTRONIC 25 produced by TAYLOR HOBSON with a measuring range up to 300 *μm*.

V. Experiment Results

Having performed the experiment by drilling holes with depth l = 3d for different parameters of the machining operation (nominal diameter, speed, feed and the angle of installation of the workpiece), the values of the axial drilling force F_3 *(N)* and the mean arithmetic deviation of the surface roughness profile R_a (*μm*) for different twist drills wear levels have been obtained. The values obtained are given in Table VI.

TABLE VI. Experiment Resuts

No.	d (mm)	n (o/min)	f (mm/rev)	ε (°)	VB = 0 mm		VB = 0,02d		VB = 0,04d	
					F_3 (N)	R_a (μm)	F_3 (N)	R_a (μm)	F_3 (N)	R_a (μm)
1.	3	300	0,03	0	243,21	0,306	348,88	0,675	410,28	0,960
2.	3	500	0,05	3	329,62	0,411	445,86	1,23	517,12	1,41
3.	3	800	0,10	5	724,04	2,61	775,32	3,25	874,82	3,71
4.	5	300	0,05	5	724,67	0,702	737,62	0,825	989,43	1,53
5.	5	500	0,10	0	1059,7	2,58	1271,49	2,88	1296,40	3,25
6.	5	800	0,03	3	407,76	1,54	412,21	1,81	416,65	2,07
7.	8	300	0,10	3	1817,08	3,08	1842,61	3,24	2028,99	3,85
8.	8	500	0,03	5	710,80	1,88	1017,82	2,99	1040,07	4,00
9.	8	800	0,05	0	832,14	2,86	867,66	3,29	965,86	4,46

VI. Models Development

The experimental results for VB = 0,02d were used along with the values of the parameters b_0, ..., b_5 obtained by means of the least squares method to form a model of multiple linear regression (MLRM):

$$\hat{R}_a = b_0 + b_1 \cdot d + b_2 \cdot n + b_3 \cdot s + b_4 \cdot \varepsilon + b_5 \cdot F_3 .$$

The parameters of the model with standard regression error s, the coefficient of determination R^2, the adjusted coefficient of determination $\overline{R}^2$ and the standard parameter error S_{b_j} (j = 1, ..., 5) are given in Table VII.

TABLE VII. Multiple Linear Regression Model Parameters with Axial Drilling Force for TD NB Variant Drilling in the Test Tubes 28 HRC Hardness

Model parameter	Parameter value	S_{b_j}	$t_j = \frac{b_j}{S_{b_j}}$	s
				0,515631635
b_0	-1,247352303	-	-	R^2
b_1	-0,06714737	0,083646497	-0,802751737	
b_2	0,003859932	0,000836465	4,614576426	0,918200815
b_3	-6,79879202	5,838378579	-1,164500028	$\overline{R}^2$
b_4	-0,002993561	0,083646497	-0,035788237	
b_5	0,002572038	0,000382718	6,720446502	0,781868839

Given that all the values $\left|t_j\right| < t$ for the significance level p = 0,001, the estimation of the dependent variable R_a based on the variables d, n, f, ε and F_3 makes sense.

After the formation of the multiple linear regression model, a transformed multiple nonlinear regression model is formed as follows:

$$log\,\hat{R}_a = log\,b_0 + b_1\,log\,d + b_2\,log\,n + b_3\,log\,s + b_4\,log\,\varepsilon + b_5\,log\,F_3\,.$$

The parameters of the transformed model with standard regression error s, the coefficient of determination R^2, the adjusted coefficient of determination $\overline{R}^2$ and the standard parameter error S_{b_j} (j = 1, ..., 5) are given in Table VIII.

TABLE VIII. Transformed Regression Model Parameters with Axial Drilling Force for TD NB Variant Drilling in the Test Tubes 28 HRC Hardness

Model parameter	Parameter value	S_{b_j}	$t_j = \frac{b_j}{S_{b_j}}$	s
				0,106950387
log b_0	-6,509728393	-	-	R^2
b_1	-0,334062021	0,204943271	-1,630021905	
b_2	1,046248025	0,204943271	5,105061606	0,943310952
b_3	-0,322109369	0,166372743	-1,936070551	$\overline{R}^2$
b_4	-0,000393794	0,007885879	-0,049936587	
b_5	1,320569484	0,158404252	8,33670475	0,848829204

Transformation of the obtained model resulted in the multiple nonlinear regression model (MNRM) with axial drilling force for twist drill drilling operation in 28 HRC hardness test tubes:

$$\hat{R}_a = b_0 \cdot d^{b_1} \cdot n^{b_2} \cdot s^{b_3} \cdot \varepsilon^{b_4} \cdot F_3^{b_5}\,.$$

Formation of the model based on artificial neural networks (ANNM) with multiple inputs (nominal diameter of the twist drill, the speed, the feed, the angle of installation of the workpiece, and axial force) and one output (the mean arithmetic deviation of surface roughness) was conducted using the Backpropagation artificial neural network with two hidden layers with sigmoidal transfer functions and a linear transfer function in the output layer.

Training, validation and testing of the neural network was performed with input combinations of the machining process parameters and the axial drilling force obtained for twist drills flank wear values of VB = 0 mm and VB = 0,04d. The least errors in training, validation and testing were achieved by a neuron network of 15 neurons in the first hidden layer, 10 neurons in the second hidden layer (Fig. 3), and the learning function LEARNGDM.

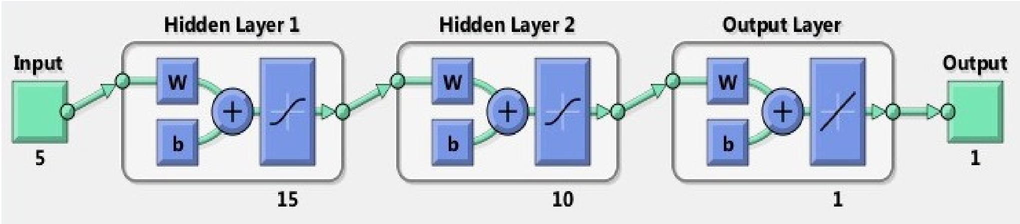

Fig. 3. Architecture of trained artificial neural network

Based on all input combinations and values of the axial drilling force obtained for the twist drills wear values of *VB* = 0,02*d* the trained artificial neural network was simulated. Comparative results of the experiment, regression models and the results obtained by simulating the trained artificial neural network are given in Table IX.

TABLE IX. Comparative Analysis of the Experiment Results and Models with Axial Drilling Force for TD NB Variant Drilling in the Test Tubes 28 HRC Hardness

No.	R_a (µm)	R_a (µm) – Model results			Model error (%)		
		MLRM	MNRM	ANNM	MLRM	MNRM	ANNM
1.	0,675	0,402553725	0,594873774	0,70322	40,362411	11,870552	4,180740741
2.	1,23	1,279019702	1,180354138	1,047	3,9853417	4,03624891	14,87804878
3.	3,25	2,938455912	3,2050161	3,0198	9,585972	1,38411998	7,083076923
4.	0,825	1,117169202	1,133513045	0,7506	35,414449	37,3955206	9,018181818
5.	2,88	2,937317373	3,203898677	3,1618	1,9901866	11,2464818	9,784722222
6.	1,81	2,352131193	1,729480948	1,7266	29,952	4,44856643	4,607734807
7.	3,24	3,423850341	2,59668921	3,1769	5,6743932	19,8552713	1,947530864
8.	2,99	2,544374144	2,981757721	3,8302	14,903875	0,2756615	28,10033445
9.	3,29	3,195128408	3,379469916	3,2673	2,883635	2,71945034	0,689969605
Model mean error (%)					16,083585	10,359097	8,921148912

VII. CONCLUSION

Besides its dependence on the input parameters of the machining operations, the quality of the machined surface, which is most often monitored through the mean arithmetic deviation of the surface roughness profile, depends on the machining tool wear level which can be indirectly monitored by measuring the parameters correlated with the tool wearing (the force, the torque, the acoustic emission level).

Development of multiple regression models and the model based on artificial neural networks, which establish the connection between the input parameters of the machining process and the tool wear on one side and the machined surface quality on the other by using indirect parameters, enables prediction of the machined surface quality during machining process based on the information about the parameters in correlation with the tool wear.

Comparative analysis of the developed prediction models leads to the conclusion that the model based on artificial neural networks gives the best results.

REFERENCES

[1] A. Çiçek, T. Kivak and G. Samtaş, „Application of Taguchi Method for Surface Roughness and Roundness Error in Drilling of AISI 316 Stainless Steel“, Strojniški vestnik - Journal of Mechanical Engineering, vol. 58, no. 3, 2012, pp. 165-174
[2] L.L.R. Rodrigues, A.N. Kantharaj, B. Kantharaj, W.R.C. Freitas and B.R.N. Murthy, „Effect of Cutting Parameters on Surface Roughness and Cutting Force in Turning Mild Steel“, Research Journal of Recent Sciences, vol. 1, no.10, 2012, pp. 19-26
[3] B.V. Raghunandan, S.L. Bhandarkar and K.S. Pankaj, „An Experimental Mathematical Modelling of Surface Roughness in Turning Operation of En19 with Carbide Tool“, International Journal of Mechanical Engineering and Research, vol. 3, no. 5, 2013, pp. 495-502
[4] F. Ficici, S. Koksal and M.C. Karacadag, „Optimization of Cutting Parameters for Surface Roughness of Stainless Steel in Drilling Process“, International Journal of Science and Advanced Technology, vol. 2, no. 3, 2012, pp. 114-121
[5] A. Rashid and A. Lani, „Surface Roughness Prediction for CNC Milling Process using Artificial Neural Network“, In Proceedings of the World Congress on Engineering, London, 2010.
[6] G. Šimunović, T. Šarić and R. Lujić, „Application of neural networks in assessing the quality of the machined surface“, Tehnički vjesnik, vol. 16, no. 2, 2009, pp. 43-47
[7] M.N. Konanki and R.R. Sadineni, „ANN Based Surface Roughness Prediction In Turning Of AA 6351“, International Journal of Engineering Research and Applications, vol. 3, issue 4, 2013, pp.1455-1459
[8] B. Nedić, B. Tadić and Z. Đorđević, „Some results of testing the impact of the tool wear on cutting forces and the machined surface quality“, Tribology in industry, no. 4, 1991, pp. 107-114

[9] O. Spaić and B. Marinović, „Influence of Wearing Drills on Drilling Axial Force“, 1st International Scientific Conference Cometa 2012, Jahorina
[10] Y. Xu, K. Hiroyuki and Z. Wei, „Back Propagation Wavelet Neural Network Based Prediction of Drill Wear from Thrust Force and Cutting Torque Signals“, Computer and Information Science, vol. 2, no. 3, 2012, pp. 75-86
[11] M. Lovroć, J. Komić and S. Stević, „Statistical analysis - methods and application“, Faculty of Economics, Banja Luka, 2006.
[12] M. Kostić, „Methods of statistical analysis“, Senior Business School Belgrade, Belgrade, 1996.
[13] M. Mijanović, „Statistical methods in anthropological sciences“, University of Montenegro, Podgorica, 1997.
[14] B. Dalbelo - Bašić, M. Čupić and J. Šnajder, „Artificial neural networks“, Faculty of Electrical Engineering and Computing, Zagreb, 2008.
[15] T.M. Hagan, B.H. Demuth, H.M. Beale, O. De Jesús, „Neural Network Design“, 2nd Edition, eBook, Available at: http://hagan.okstate.edu/NNDesign.pdf (Downloaded: 25 January 2018)
[16] M. Cavazzuti, „Optimization Methods: From Theory to Design“, Springer-Verlag Berlin Heidelberg, 2013.

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