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MODELS FOR PREDICTING THE MAXIMUM HEIGHT OF THE SURFACE ROUGHNESS PROFILE BASED ON AXIAL DRILLING FORCE

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Abstract: *The functional performance and in-service quality of products are strongly influenced by surface roughness, which is a direct outcome of material removal processes. In general, surface roughness is function by the input parameters of the machining process and the extent of tool wear, the increase of which leads to an increase cutting forces, torque, acoustic emission level, vibrations, and temperature. Finding the dependence between machining parameters, tool wear indicators, and surface roughness parameters enables real-time prediction of surface quality and contributes to appropriate processing quality. In this study, based on data obtained through experiment conducted using the Taguchi design of experiment, predictive models were developed using multiple regression analysis and artificial neural networks (ANN). These models establish a relationship between input drilling parameters, axial drilling force, and the maximum height of the surface roughness profile.*

Keywords: *Drilling, Surface roughness, Axial force, Multiple regression, ANN*

1. INTRODUCTION

In the manufacturing of products, particular emphasis is placed on dimensional accuracy and the surfaces roughness in terms of processing quality. Accordingly, establishing a relationship between surface roughness parameters - which serve as indicators of surface roughness - and the input parameters of the machining process, while accounting for the level of tool wear, becomes increasingly significant.

A substantial number of research has established a relationship between surface roughness - most commonly characterized by the arithmetic mean deviation of the surface roughness profile - and the parameters of the cutting process. Numerous researchers [1-5] have employed regression analysis to derive mathematical models that relate machining input parameters to surface roughness, or have utilized artificial neural networks to predict surface roughness.

Previous models demonstrated excellent performance in predicting surface roughness based on machining input parameters; however, they did not account for the combined effect of input parameters and tool wear level on surface roughness.

Tool wear, its prediction, and the establishment of correlations with measurable process parameters (such as cutting force, torque, vibrations, and acoustic emission level) have also been the subject of extensive research [6-8].

Based on conducted experimental studies and existing literature, several authors [9-11] have applied multiple regression analysis and artificial neural networks to establish relationships among machining input parameters, measurable process parameters associated with tool wear, and the arithmetic mean deviation of the surface roughness profile.

While predicting the arithmetic mean deviation of the surface roughness profile provides insight into average roughness level, in order to detect specific surface irregularities, it is also important to predict the maximum height of the surface roughness profile.

Considering the above, as well as existing models for surface roughness prediction [12, 13], this study develops models that establish a relationship between drilling process input parameters, drilling axial force, and the maximum height of the surface roughness profile.

2. EXPERIMENTAL DESIGN

The maximum height of the surface roughness profile, which results from the cutting process, is a function of the machining input parameters and the wear of the cutting tool. Considering that the input parameters of the drilling process include the nominal diameter of the twist drill (*d*), spindle speed (*n*), and feed rate (*f*), and that the angle of workpiece positioning (ε) can be considered an additional input parameter, the experiment was designed in accordance with Taguchi's orthogonal array method, with the experimental factors varied at three levels.

Given that the variation of experimental factors at three levels corresponds to Taguchi's L_9 orthogonal array with nine combinations of machining process parameters, and by treating the drilling input parameters as experimental factors, the resulting experimental design matrix is presented in the following table (Table 1).

Table 1. Experimental Design Matrix

No.	d [mm]	n [rev/mm]	f [mm/rev]	ε [°]
1.	d_1	n_1	f_1	ε_1
2.	d_1	n_2	f_2	ε_2
3.	d_1	n_3	f_3	ε_3
4.	d_2	n_1	f_2	ε_3
5.	d_2	n_2	f_3	ε_1
6.	d_2	n_3	f_1	ε_2
7.	d_3	n_1	f_3	ε_2
8.	d_3	n_2	f_1	ε_3
9.	d_3	n_3	f_2	ε_1

The specific values of the experimental factors, categorized by levels, are presented in the following table (Table 2).

Table 2. Factor Values by Levels

Level	d [mm]	n [rev/min]	f [mm/rev]	ε [°]
1.	3	300	0.03	0
2.	5	500	0.05	3
3.	8	800	0.10	5

The experiment was planned to be conducted on a CNC milling machine MILL 250, manufactured by EMCO, by drilling holes to a depth of $l = 3d$ in test tubes made of enhancement steel EN 42CrMo4, heat-treated to a hardness of 28 HRC.

Twist drills made of high-speed steel EN HS6-5-2, in black version with a cruciform blade, manufactured using grinding technology and heat-treated to a hardness of 64-68 HRC, were provided for the experimental procedure.

Measurement of flank wear on the twist drills is planned to be performed using the

GÜHRING PG 100 optical device for measuring the geometrical elements of twist drills, featuring digital readout capability.

To measure the maximum height of the surface roughness profile, the SURTRONIC 25 surface roughness tester manufactured by TAYLOR HOBSON was provided, with a measurement range up to 300 µm. For the measurement of axial drilling force, a measurement chain by KISTLER was provided, having a measuring range of up to 20,000 N.

3. RESULTS AND ANALYSIS

The experiment was conducted in accordance with the experimental design matrix, with measurements taken of the axial drilling force (F_3) and the maximum height of the surface roughness profile (R_z) after drilling with a sharp tool (VB = 0 mm), at the point when tool wear reaches the average value (VB = 0.02d), and at the point of tool blunting, when wear reaches the maximum value (VB = 0.04d).

The measurement of the maximum height of the surface roughness profile was performed at four characteristic locations by rotating the test tube by 90°, with the mean value of the measured results taken as representative.

The measurement results are presented in the following table (Table 3).

Table 3. Measurement Results

No.	VB=0 mm		VB=0.02d		VB=0.04d	
	F_3	R_z	F_3	R_z	F_3	R_z
1.	218.36	2.68	263.33	3.66	418.23	4.64
2.	275.30	4.75	356.91	5.71	456.51	6.67
3.	621.44	14.32	684.55	15.85	719.99	19.60
4.	478.05	5.07	538.26	5.93	889.86	7.51
5.	888.64	13.65	919.21	16.27	1289.59	16.55
6.	352.40	9.09	368.09	10.34	398.01	14.63
7.	1138.50	13.05	1237.37	17.10	1336.23	21.15
8.	345.76	10.61	405.10	12.71	464.44	14.80
9.	538.03	12.63	556.07	13.83	602.46	16.70

Based on the experimental results, a multiple linear regression (MLR) model and a model based on artificial neural networks (ANN) were developed.

Since the primary task in forming the multiple linear regression model involves determining the estimated values of the parameters b_0, b_1, b_2, ..., b_n, using the least squares method and utilizing the experimental results at the point of tool blunting (VB=0.04d), a model was formulated with machining process input parameters (d, n, f, ε) and axial drilling force (F_3) as inputs, in the following form:

$$\hat{R}_z = b_0 + b_1 \cdot d + b_2 \cdot n + b_3 \cdot f + b_4 \cdot \varepsilon + b_5 \cdot F_3 \quad (1)$$

The parameter values of the model, along with the regression error s, the coefficient of determination R^2, the adjusted coefficient of determination $\bar{R}^2$ and the standard error of the parameters S_{b_j} (j = 1,...,5) are presented in the following table (Table 4).

Table 4. Multiple Regression Model Parameters

Model parameter	Value parameter	S_{b_j}	$t_j = \frac{b_j}{S_{b_j}}$	s 2.7062
b_0	-8.0672	-	-	R^2
b_1	1.5805	0.4390	3.6002	
b_2	0.0104	0.0044	2.3680	0.9213
b_3	148.1374	30.6420	4.8345	$\bar{R}^2$
b_4	0.2471	0.4390	0.5628	
b_5	-0.0026	0.0026	-0.9810	0.7902

Taking into account the fact that the values are $|t_j| < t$, for a given significance level p=0.01 [14], the estimation of the dependent variable R_z based on the variables d, n, f, ε and F_3 makes sense.

The artificial neural network (ANN) model (Figure 1) with multiple inputs (d, n, f, ε and F_3) and a single output (R_z) was developed using a Backpropagation neural network consisting of two hidden layers with sigmoid transfer functions and a linear transfer function in the output layer.

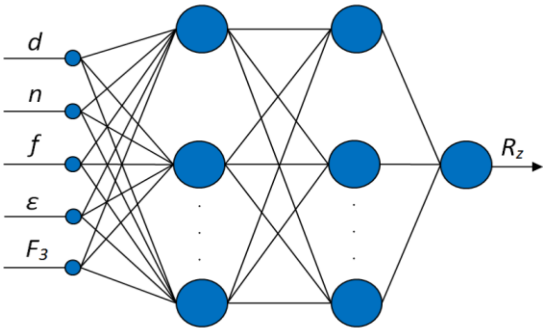

Figure 1. Artificial Neural Networks-Based Model

The model development was performed using combinations of machining input parameters and axial drilling force values obtained for different levels of flank wear on twist drills prior to tool blunting. The best training, validation, and testing results were achieved with a neural network consisting of 10 neurons in the first hidden layer and 5 neurons in the second hidden layer.
Simulation of the trained artificial neural network was conducted for all combinations of input parameters and axial drilling force values obtained at the tool blunting (VB=0.04d).

A comparative analysis of the experimental results, multiple linear regression (MLR) model results, and artificial neural network (ANN) model results is presented in the following table (Table 5).

Table 5. Comparative Analysis of Results

No.	R_z [µm]	R_z [µm] - model		Error [%]	
		MLR	ANN	MLR	ANN
1.	4.64	3.17	4.32	31.68	6.90
2.	6.67	8.85	6.22	32.68	6.75
3.	19.60	19.20	21.08	2.04	7.55
4.	7.51	9.32	7.09	24.10	5.59
5.	16.55	16.55	16.72	0.00	1.03
6.	14.63	12.32	15.88	15.79	8.54
7.	21.15	19.83	21.53	6.24	1.80
8.	14.80	14.27	14.90	3.58	0.68
9.	16.70	18.76	16.97	12.34	1.62
Average error [%]				14.27	4.49

Based on the comparative analysis of the experimental results and the models, it is observed that the individual errors of the multiple linear regression model range from 0.00% to 32.68%, while the errors of the artificial neural networks-based model range from 0.68% to 8.54%. The average error of the multiple linear regression model is 14.27%, whereas the average error of the artificial neural network model is 4.49%.

By comparing the experimental results with the model outcomes and analyzing the model errors, it is evident that better prediction accuracy is achieved using the artificial neural networks-based model. A comparative presentation of the experimental results and the aforementioned model is shown in the following figure (Figure 2).

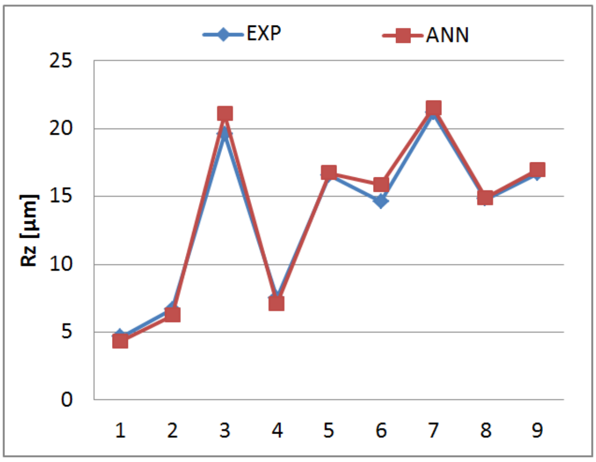

Figure 2. Comparative Presentation of Results

4. CONCLUSION

The maximum height of the surface roughness profile, as a parameter characterizing certain irregularities of the roughness profile, is a function of the machining process input parameters and the extent of tool wear which is correlated with some measurable process parameter.

By developing prediction models for the maximum height of the surface roughness profile using multiple linear regression and artificial neural networks, it is possible to predict the maximum height of the surface roughness profile as a function of the drilling process input parameters and axial drilling force.

Comparative analysis of the developed models leads to the conclusion that better prediction results are achieved using the artificial neural networks-based model.

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