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PREDICTION THE MAXIMUM HEIGHT OF ROUGHNESS PROFILE AS A FUNCTION OF TOOL WEAR USING ARTIFICIAL NEURAL NETWORKS

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Abstract: *By training artificial neural networks based on data obtained through experiment conducted using the Taguchi design in drilling process, this study developed models for predicting the maximum height of roughness profile as a function of tool wear. The development of models with multiple inputs and a single output was performed using Backpropagation artificial neural networks with one and two hidden layers, employing sigmoid transfer functions in the hidden layers and a linear transfer function in the output layer. During the models development, the input parameters of the drilling process and the tool wear values before tool blunting were used as network inputs, while the maximum height of roughness profile was used as the network output. A comparative analysis of models errors, calculated based on experimental values and predicted maximum height of roughness profile values for given input parameters and wear at the moment of tool blunting, led to the conclusion that the best results were obtained using the artificial neural network model with two hidden layers, employing sigmoid transfer functions in the hidden layers and a linear transfer function in the output layer.*

Keywords: *Prediction, Roughness, Tool wear, Artificial neural networks*

1. Introduction

Numerous studies aim to establish surface roughness prediction models that are based on the input parameters of the cutting process. Surface roughness prediction is most commonly performed using mathematical models obtained through the application of multiple regression statistical method and models developed using artificial neural networks (ANN models). Since regression models require a more detailed statistical analysis with a large amount of data, models based on artificial neural networks represent a much more suitable approach for surface roughness prediction.

Rashid and Lani (2010) developed a mathematical model using multiple regression and applied an artificial neural network to predict surface roughness in aluminum milling. Their models linked surface roughness, expressed through the arithmetic mean deviation of the roughness profile (R_a), with the input parameters of the machining process. The mathematical model yielded results with an average error of 13.3%, whereas the artificial neural network predicted results with an average error of 6.42%, leading to the conclusion that the artificial neural network achieved better

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accuracy in surface roughness prediction.

Konanki and Sadineni (2013), based on data obtained during the turning of AA 6351 alloy and through an experiment conducted using the Taguchi method, developed a surface roughness prediction model based on artificial neural networks. The model was developed using a multilayer artificial neural network, with the input machining parameters as network inputs and the arithmetic mean deviation of the roughness profile (R_a) as the network output. Testing of the model resulted in an average prediction error of 2.24%, yielding an acceptable surface roughness prediction model.

Previous models have provided a solid foundation for surface roughness prediction based on artificial neural networks, but they have not considered the coupled effect of machining process input parameters and tool wear on surface roughness (Melkamu, 2025).

Mathew et al. (2008) demonstrated that tool wear in milling medium-carbon steel EN-8 can be correlated with acoustic emission level. Bhaskaran et al. (2012) investigated the impact of tool wear on surface roughness and acoustic emission signal during the turning of high-alloy tool steel AISI-D3 (60 HRC) and observed that increased tool wear leads to an increase in surface roughness parameters. Moreover, they noticed that upon reaching a certain wear threshold, there is a sudden increase in specific acoustic emission parameters and surface roughness values.

Krivokapić et al. (2015) concluded that by applying regression analysis and artificial neural networks to data obtained from experiment conducted using the Box-Wilson plan during the drilling of EN 42CrMo4 steel (thermally treated to a hardness of 43-45 HRC), models can be developed for monitoring measurable process parameters (axial force and torque) that correlate with tool wear. By establishing a relationship between these parameters and the arithmetic mean deviation of the roughness profile, surface roughness can be predicted.

Tamang and Chandrasekaran (2015) developed a model using regression analysis and an artificial neural network model with multiple outputs, linking the input parameters of the turning process (of a composite material with an aluminum metal matrix) with the arithmetic mean deviation of surface roughness and tool wear. By comparing experimental results with ANN model predictions, they found that the artificial neural network achieved over 95% accuracy for predicting the arithmetic mean deviation of the roughness profile and over 92% accuracy for predicting tool wear.

Vučurević et al. (2018) developed multiple regression models and an artificial neural network model based on experimental data for the arithmetic mean deviation of the roughness profile and axial cutting force, obtained through a Taguchi experimental plan during drilling of EN 42CrMo4 steel (thermally treated to a hardness of 28 HRC). Their models established a connection between machining process input parameters, axial cutting force (which correlates with tool wear), and surface roughness. A comparative analysis of the developed prediction models led to the conclusion that the best results were achieved with the artificial neural network model.

Krivokapić et al. (2020), using the Taguchi experimental plan for drilling EN 42CrMo4 steel (thermally treated to a hardness of 28 HRC), developed models that established relationships between machining process input parameters and torque, a measurable parameter associated with tool wear, with the arithmetic mean deviation of the roughness profile. Comparing experimental results with those from multiple regression models and ANN model, they concluded that the ANN model provided the best results, with an average prediction error of 2.13%.

Lin et al. (2020) modeled the arithmetic mean deviation of the roughness profile based on cutting parameters, both with and without considering vibrations during face milling of aluminum alloy Al6061. A comparative analysis of the multiple regression prediction model and the artificial neural network model led to the conclusion that the ANN model based on cutting parameters with vibration inclusion achieved the highest average prediction accuracy (93.14%). Supporting this, Abidi and Boulanouar (2021) observed a strong correlation between tool wear and cutting vibrations during the turning of AISI 1045 steel.

Cao et al. (2021) investigated the effect of tool wear during the turning of two types of steel (30CrMnSi and 45CrMnSi) using different tools and concluded that relative hardness (the ratio of the workpiece material hardness to the cutting tool hardness) is the primary factor affecting the tool edge wear rate, leading to a gradual deterioration in workpiece surface roughness. Earlier, in support of the previous one, Vučurević et al. (2019) investigated the influence of tool wear on the surface roughness when drilling steel EN 42CrMo4. They came to the conclusion that tool wear during the machining process has an almost uniform effect on the surface roughness. Furthermore, through a comparative analysis of the value of the mean arithmetic deviation of the roughness profile at the moment of blunting of the tool and at the beginning of the process, they came to the conclusion that wear at the moment of blunting of the tool has the greatest negative impact for the maximum values of the diameter of the twist drill and the spindle speed.

Tomov et al. (2022) applied and proposed two different methodologies for mathema-tical modeling of surface roughness parameters during the turning of EN C55 steel (hardness 53±1 HRC). By developing models for multiple roughness parameters, they found that mathematical models can adequately predict surface roughness parameters, such as the arithmetic mean deviation of the roughness profile (R_a) and the maximum height of roughness profile (R_z), for the same machined surface.

Li et al. (2024) investigated the influence of tool wear and workpiece diameter on surface roughness during the turning of 06Cr19Ni10 steel. In addition to concluding that workpiece diameter is an important factor affecting vibration magnitude and, consequently, surface roughness, they developed multiple regression models for surface roughness prediction based on cutting parameters, tool wear, and workpiece diameter. The best surface roughness prediction results were achieved using an exponential empirical model with an average prediction accuracy of 91.04%.

Concerning modern manufacturing systems, product quality is strongly influenced by the stability and capability of machining processes. Surface quality, commonly evaluated through surface roughness parameters, represents one of the key indicators of machining performance because it directly affects functional properties, service life, friction behavior, and reliability of manufactured components as well as quality at all. Since tool wear could be considered is an inevitable phenomenon during machining and has a significant impact on the deterioration of surface quality, accurate prediction of roughness parameters enables better process control, timely tool replacement, and improvement of overall manufacturing quality. Therefore, the integration of artificial intelligence methods into machining process monitoring represents an important approach toward achieving higher quality, efficiency, and reliability in modern production systems (Atsegeba et al., 2025a; Atsegeba et al., 2025b).

Having in mind the context of Industry 4.0 and intelligent manufacturing, maintaining consistent product quality requires continuous monitoring and prediction of machining process behavior (Singh et al., 2025). Traditional quality inspection methods are usually performed after the machining operation, and this approach limits the possibility of preventing defects during production. Predictive models based on artificial neural networks provide an opportunity to estimate surface quality parameters in real time by establishing complex relationships between process conditions, tool degradation, and final product characteristics. This approach supports proactive quality assurance, minimizes the occurrence of non-conforming parts, and contributes to improved productivity, process reliability, and sustainable manufacturing performance (Abdullah & Hadi, 2025; Atsegeba 2025).

Considering the aforementioned studies, the present research aimed to develop a model for predicting the maximum height of roughness profile (R_z) as a function of tool wear using artificial neural networks based on experimental data obtained during drilling.

2. Design of experiment

Considering the fact that the maximum height of the surface roughness profile (R_z) depends on several input parameters of the drilling process and is influenced by tool wear, the experiment was planned to be conducted using the Taguchi orthogonal experimental design, with variation of experimental factors (input parameters) at three levels.

Table 1. Experimental design matrix

No.	d	n	f	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

Since the input parameters of the drilling process include the twist drill diameter (d), spindle speed (n), and feed (f), and an additional input parameter can be the workpiece positioning angle (ε), the variation of experimental factors at three levels corresponds to the Taguchi orthogonal matrix L_9 (Cavazzuti, 2013), which consists of nine combinations of machining process parameters. Applying this approach resulted in the experimental design matrix (Table 1).

The values of the experimental factors, including the nominal diameter of the twist drill, cutting parameters, and the workpiece positioning angle, by different levels, are presented in the following table (Table 2).

Table 2. Values of experimental factors

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 previous values of the experimental factors were adopted based on the recommendations of the twist drill manufacturer.

The experiment is planned to be conducted by drilling holes with a depth of l=3d in test tubes made of enhancement steel EN 42CrMo4 with a hardness of 17 HRC, whose dimensions are provided in the following table (Table 3).

Table 3. Test tubes dimensions

Twist drill	Drilling depth [mm]	Test tube diameter [mm]	Test tube thickness [mm]
Ø 3	9	Ø 60	15
Ø 5	15		20
Ø 8	24		30

The chemical composition of the EN 42CrMo4 steel, which is classified as a high-quality steel with good strength, toughness, and corrosion resistance, is provided in the following table (Table 4).

Table 4. Composition of EN 42CrMo4 steel (%)

Element	C	Si	Mn	P	S	Cr	Mo
Min	0.38	0.15	0.5	-	-	0.9	0.15
Max	0.45	0.4	0.8	0.035	0.035	1.2	0.3

The holes drilling is planned to be performed using twist drills DIN 338 ø3, DIN 338 ø5, and DIN 338 ø8, in black version with normal blade, manufactured using grinding technology and thermally treated to a hardness of 64-68 HRC from high-speedsteel EN HS6-5-2, whose chemical composition is provided in the following table (Table 5).

Table 5. Composition of EN HS6-5-2 steel (%)

El.	C	W	Mo	Cr	V	Si	Mn	P	S
Min	0.82	5.5	4.5	3.8	1.75	0.2	0.15	-	-
Max	0.9	6.75	5.5	4.4	2.2	0.45	0.4	0.03	0.03

The experiment is planned to be carried out on a CNC milling machine MILL 250, manufactured by EMCO, with EMCO WinNC numerical control, capable of reaching a maximum spindle speed of 10 000 rev/min (rpm) and a range of auxiliary movement speeds from 0 to 10 m/min (Figure 1).

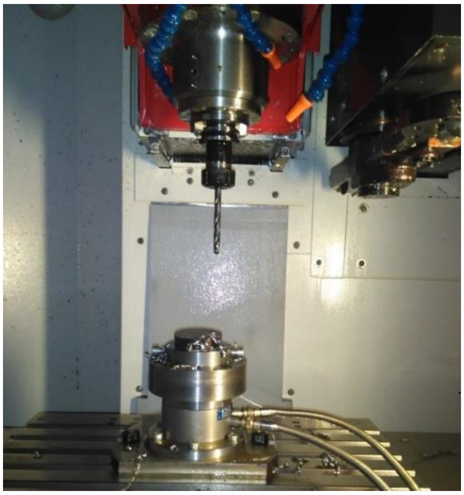

Figure 1. CNC milling machine with tool and test tube

Figure 2. Measuring instrument SURTRONIC 25

The measurement of the maximum height of the surface roughness profile is planned to be performed with the SURTRONIC 25 measuring instrument, manufactured by TAYLOR HOBSON, with a measurement range of up to 300 μm (Figure 2).

For measuring the wear size on the flank surface of the twist drill, the use of the optical device for measuring the geometric elements of twist drills GÜHRING PG 100 (Figure 3) is planned, with the capability of digital reading of the measured values.

Figure 3. Device for measuring geometric elements GÜHRING PG 100

3. Results and discussion

The measurement of the maximum height of the surface roughness profile (R_z) was carried out at the beginning of the process, at the moment the tool wear reached a certain size, and at the moment the tool blunting. The tool wear size was measured on the flank surfaces along the main cutting edges of the tool (twist drill), and the following flank wear used as criteria for blunting (VB = 0.04d):

- VB = 0.12 mm for the twist drill DIN 338 ø3,
- VB = 0.20 mm for the twist drill DIN 338 ø5,
- VB = 0.32 mm for the twist drill DIN 338 ø8.

The overview of the average values of the maximum height of the surface roughness profile (R_z), obtained by measuring at four points by rotating the test tube by an angle of 90°, at characteristic moments related to the tool wear size, is given in the following table (Table 6). Before the measurements, the measuring device was calibrated using a reference plate type 112/1534 with the arithmetic mean deviation of the roughness profile R_a = 6 μm.

Table 6. Measurement results

No.	R_z [μm]		
	VB = 0 mm	VB = 0.02d	VB = 0.04d
1.	1.99	3.60	5.20
2.	6.28	7.79	8.03
3.	13.70	16.58	19.45
4.	6.21	6.41	8.40
5.	16.23	17.42	18.60
6.	8.84	13.15	13.38
7.	11.01	13.73	15.43
8.	12.35	13.83	17.15
9.	15.20	20.10	24.63

Using experimental results, prediction models based on artificial neural networks were developed, with the maximum height of the surface roughness profile (R_z) as the objective function, input combinations of processing parameters, and wear values on the flank surfaces of twist drills before tool blunting.

The development of the multi-input models (nominal diameter of the twist drill, spindle speed, feed, workpiece positioning angle, and tool wear) and a single output (the maximum height of the surface roughness profile) was carried out using Backpro-pagation artificial neural networks with one and two hidden layers, with sigmoid transfer functions and a linear transfer function in the output layer (Figure 4).

The simulation of the prediction models obtained by training the artificial neural networks was carried out for all combinations of input parameter values and wear values at the moment of tool blunting (VB = 0.04d). The data used for the simulation are provided in the following table (Table 7).

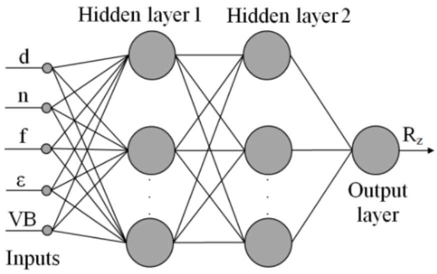

Figure 4. Artificial neural network model

Table 7. Data for simulation

No.	d [mm]	n [rpm]	f [mm/rev]	ε [°]	VB [mm]
1.	3	300	0.03	0	0.12
2.	3	500	0.05	3	0.12
3.	3	800	0.10	5	0.12
4.	5	300	0.05	5	0.20
5.	5	500	0.10	0	0.20
6.	5	800	0.03	3	0.20
7.	8	300	0.10	3	0.32
8.	8	500	0.03	5	0.32
9.	8	800	0.05	0	0.32

The models development was first carried out with artificial neural networks with one hidden layer, initially with a network having 5 neurons in the hidden layer (network type 5-1), and then with 10 neurons in the hidden layer (network type 10-1). Subsequently, the development of the model with two hidden layers was carried out, with 10 neurons in the first hidden layer and 5 neurons in the second hidden layer (network type 10-5-1). All artificial neural networks achieved good training results (R=0.99958-0.99996).

Table 8. Simulation results and errors

No.	5-1		10-1		10-5-1	
	R_z[μm]	δ [%]	R_z[μm]	δ [%]	R_z[μm]	δ [%]
1.	4.51	13.27	4.70	9.62	4.87	6.35
2.	8.95	11.46	7.48	6.85	8.15	1.49
3.	19.09	1.85	19.04	2.11	19.29	0.82
4.	8.84	5.24	8.80	4.76	8.68	3.33
5.	18.54	0.32	18.47	0.70	19.05	2.42
6.	13.88	3.74	13.25	0.97	12.54	6.28
7.	15.88	2.92	15.55	0.78	14.78	4.21
8.	15.54	9.39	17.71	3.27	15.86	7.52
9.	25.88	5.08	22.23	9.74	23.77	3.49
Δ[%]	5.92		4.31		3.99	

The simulation results (R_z), simulation errors (δ), and mean errors (Δ) of the models are presented in the following table (Table 8).

By comparing the experimental results with those from the models based on artificial neural networks, it is observed that for the 5-1 network type model, the individual errors range from 0.32% to 13.27%, with an average error of 5.92%. For the 10-1 network type model, the individual errors range from 0.70% to 9.74%, with an average error of 4.31%. The individual errors for the 10-5-1 network type model range from 0.82% to 7.52%, with an average error of 3.99%.

Looking at the average errors, it can be seen that the models with the 10-1 and 10-5-1 network types have average errors of less than 5%, with the range of individual prediction errors being smaller for the 10-5-1 network type model. A comparative view of the errors from these models is shown in the next figure (Figure 5).

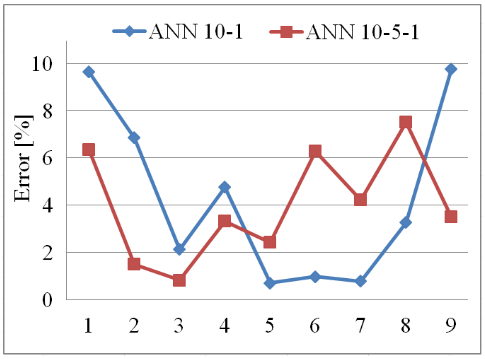

Figure 5. The comparative view of errors

Considering the above, it can be seen that the smaller individual errors are on the side of the 10-5-1 network type, meaning that this network provides the best prediction results.

The comparative view of experimental results and the results obtained from the 10-5-1 network simulation is shown in the following figure (Figure 6).

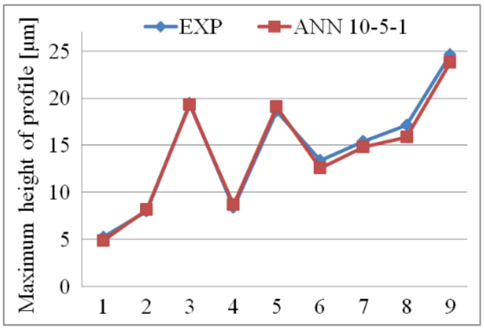

Figure 6. Comparative view of results

4. Conclusion

Based on the previous findings, this research demonstrates that artificial neural networks can be used to develop prediction models for the maximum height of roughness profile (R_z) as a function of tool wear and input parameters of the drilling process.

Through a comparative analysis of the experimental results and the results obtained from the models simulation, for input data at the point of tool blunting, it was concluded that the best results are provided by the artificial neural network model with two hidden layers with sigmoid transfer functions and a linear transfer function in the output layer, specifically in this case, the model with the network type 10-5-1.

The developed artificial neural network model contributes not only to the prediction of surface roughness but also to the improvement of machining quality control. This is one very important contribution of the research. Considering both machining parameters and tool wear as input variables, the proposed approach enables more reliable estimation of surface quality degradation during the tool life cycle. This provides a basis for implementing intelligent manufacturing strategies, reducing the risk of producing components with unacceptable surface characteristics, and supporting quality-oriented optimization of machining processes.

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