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Research article

The Modelling of Surface Roughness After the Turning of Inconel 601 by Using Artificial Neural Network

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A B S T R A C T

This research includes longitudinal turning of Inconel 601 in a dry environment with PVD coated cutting inserts. Turning was performed for different levels of cutting speeds, feeds, depth of cuts and corner radius. After turning, the arithmetical mean surface roughness was measured. Mean arithmetic surface roughness values ranging from 0.156 µm to 6.225 µm were obtained. Based on the obtained results, an artificial neural network (ANN) was created. This ANN model was used to predict surface roughness after machining for different variants of input variables. Performance evaluation of the generated model was performed on the basis of additional - confirmation experiments. The mean absolute errors are 0.005 µm and 0.012 µm for the training and confirmation experiments, respectively. The mean percentage errors are 0.894 % and 1.303 % for the training and confirmation experiments, respectively. The obtained results showcase the possibility of practical application of the developed ANN model.

1. INTRODUCTION

By turning, workpieces can be machined to the final size and in the final quality of the machined surface. Finish turning of the workpieces avoids, or reduces, subsequent finishing treatments, which contributes to the reduction of associated costs. Surface roughness after turning is one of the most relevant parameters in terms of quality assessment, and it has a great influence on the performance and correct functioning of assemblies. Surface roughness is one of the most commonly used quality indicators, and is just as important as dimensional accuracy, geometrical tolerances and product specifications. Workpiece material, cutting tools, fixtures, machining parameters and machining conditions have a large influence on surface roughness. Workpieces made of different materials are machined by turning.

The problem is significantly complicated if nickel-based alloys are machined by turning. One of these is Inconel 601. It is a relatively expensive material that is difficult to machine with intensive wear of the cutting tool and long-term machining time, which results in a number of negative aspects. Therefore, predicting the machined Inconel surface roughness within acceptable tolerances can improve machining efficiency and reduce costs.

In the previous period many researchers have analyzed surface roughness produced during turning of lnconel. Settineri [1] presented results obtained by turning lnconel 718 with coated inserts produced by PVD process. Three dedicated coatings, TiN+AITiN, TiN+AITiN+MoS_2 and CrN+CrN:C+C, applied by PVD on WC-Co inserts. AITiN-based coatings with an additional layer of MoS_2, exhibited good performances in both dry and minimum quantity lubrication (MQL) condition. Tazehkandi et al. [2] investigated effect of machining parameters (cutting speed, feed and depth of cut) on surface roughness. The results were analysed using response surface methodology (RSM) and analysis of variance (ANOVA), and mathematical models for surface roughness were proposed. Results indicated that feed and cutting speed were the most effective parameters on the surface roughness. Hua and Liu [3] investigated the effects of cutting speed, feed and corner radius on surface roughness of Inconel 718 during dry turning. The results indicate that the feed and the corner radius had dominant effect on the surface roughness. Yildirim et al. [4] focused on the development of nano MQL by adding hexagonal boron nitride (hBN) nanoparticles compared to pure MQL and dry machining in turning of Inconel 625. Tool life, surface roughness and tool wear were analyzed. The results showed that; 0.5 vol% hBN nanofluid was produced promising results for low surface roughness and high tool life. Deshpande et al. [5] used artificial neural network to predict surface roughness using machining parameters, force, sound and vibration in turning of Inconel 718. Experiments were performed by using cryogenically treated and untreated inserts. The models estimated surface roughness with more than 90% accuracy. Gurgen et. [6] investigated the influences of feed, corner radius, and insert coating methods, in the turning operation of Inconel 718, on the surface roughness and tool wear. The results showed that surface roughness was reduced using low feed and large corner radius. Furthermore, TiAlN coated inserts with PVD method provided better surface finish than TiCN-Al_2O_3-TiN coated inserts with CVD method. Xu et al. [7] analysed the influence of ultrasonic vibration-assisted turning on surface roughness and chip shape. Results indicated that ultrasonic amplitude exert considerable influences and that it can improve surface roughness. Bertolini et al. [8] evaluated the effect of MQL on the turning performances of Inconel 718 compared to dry and wet lubrication conditions. The feasibility of using graphene nanoplatelets as additives to a vegetable oil to form MQL mist was assessed. Results showed that the use of the nanofluid with the lowest graphene nanoplatelets size provided the best surface integrity compared to the ones obtained when using just MQL without any additive and wet lubricating conditions. Mou and Zhu [9] compared the vibration acceleration, surface roughness, and tool wear of liquid nitrogen (LN_2) machining with dry machining. Use of LN_2 improved the quality of the machined surface, reduced the tool–chip interface temperature and tool wear. Pinheiro et al. [10] evaluated turning of Inconel through the influence analysis of cutting speed, feed and lubrication parameters. Results showed that the feed increase led to an increase of surface roughness and tool wear. Yagmur [11] investigated tool life, tool wear, surface roughness and cutting forces in turning Inconel 625 under different cooling conditions. Experiments were carried out under three different cutting conditions (dry, MQL, and vortex cooling methods). The best values for surface roughness were obtained with MQL. Dhananchezian [12] focused on experimental investigation for the varying cutting speed on temperature, surface finish, insert and chip form while turning Inconel 600 using TiAlN coated insert. A lowest surface roughness value was observed for the cutting velocity of 102 m/min. In all the cutting trials, the chips obtained were long and continuous. Akgun and Demir [13] focused on developing the mathematical model (by regression analysis) of surface roughness in the turning of Inconel 625 with cryogenically treated tungsten carbide inserts. It has been observed that the cutting speed has a maximum contribution on surface roughness. Khanna et al. [14] examined energy consumption, chip reduction coefficient and surface roughness at different material removal rates (MRR) during turning of Inconel 718 under different cutting conditions (dry, wet and cryogenic). Surface roughness values for cryogenic turning were reduced in comparison to dry and wet turning at various MRR. Gong et al. [15] focused on turning Inconel 718 using different sustainable lubricating-cooling techniques. Cryogenic machining, MQL and nanofluid MQL were applied and their performances evaluated in comparison with dry and wet machining. The experimental results revealed that cryogenic machining offered overall better performances when compared to dry, wet, MQL and nanofluid MQL strategies: lower surface roughness, fewer surface defects and lower chip compression ratio were observed. Veerappan et al. [16] machined Inconel 600 in dry condition with cubic boron nitride (CBN) tool. The ANOVA was adopted to establish the correlation between the machining parameters and response parameter. Linear regression equation for surface roughness were used to predict the responses. ANOVA results for surface roughness concluded that cutting speed has 95% contribution followed by feed 4% and depth of cut 1%. Yashwant Bhise and Jogi [17] studied the effect of cutting speed and feed on surface roughness during turning of Inconel X-750 under dry environment by using PVD TiAlN coated negative inserts with small tool nose radius of 0.4 mm. The feed has a greater impact on surface roughness. Tan et al. [18] investigated the effects of various turning parameters on the surface roughness for ceramic and carbide inserts. A quadratic surface roughness response model incorporating the cutting speed, depth of cut, and feed was developed. The results show that a smoother, more uniform surface was obtained when using a ceramic insert. Boumaza et al. [19] investigated the application of three multi-objective optimization techniques (TOPSIS, DEAR and GRA) in order to achieve the best parameters represented by the surface roughness, the tool wear and the MRR during the turning of Inconel 718 with a composite ceramic cutting tool following a Taguchi plan. The objective was to find out the best combination of the cutting speed, the feed, the depth of cut and the corner radius. The results achieved to demonstrate the effectiveness of three methods that have led to similar results represented by the optimal parameters. Hao et al. [20] established a multi input single output (MISO) multivariate Gaussian process regression (GPR) surface roughness prediction model with cutting speed, depth of cut, feed and rake angle as input variables and surface roughness as output variable. The experimental results showed that the average relative error of MISO multivariate GPR surface roughness prediction model was 1.5%.

As it can be seen, different techniques and methods are used to study the surface roughness during the Inconel turning process. The experimental approach, as the basis of scientific research, is increasingly supplemented with modeling and optimization methods. Response surface methodology [21], artificial neural network [22], fuzzy method [23], gray relational analysis [24], particle swarm optimization [25] and genetic algorithm [26] are widely used to reduce the cost and time of experimental research.

Unlike in the previous research, the goal of this research is to model the final turning process of Inconel 601, and develop an adequate model for predicting surface roughness. Modeling of the turning process was performed using an artificial neural network (ANN). The input variables are cutting speed, feed, depth of cut, and corner radius, and the output variable is surface roughness. The assessment of the possibility of predicting the output results using ANN was performed by comparing the measured and predicted values of the surface roughness, and it was quantitatively performed by calculating the percentage and absolute errors.

2. METHODOLOGY

Figure 1 shows the methodology applied in this research.

The research was conducted on workpieces made of Inconel 601 whose chemical composition is: (58–63) % nickel, (21–25) % chromium, (1–1.70) % aluminum, ≤1 % copper, ≤1 % manganese, ≤0.50 % silicon, ≤0.10 % carbon, ≤0.015 % sulphur and balanced iron. The physical and mechanical characteristics of steel Inconel 601 are: density = 8.11 g/cm^3, melting point = 1349 °C, tensile strength = 760 MPa, yield strength = 450 MPa, elongation at break = 42 %, brinell hardness =160 HB, thermal expansion coefficient = 13.75 μm/m°C and thermal conductivity = 11.2 W/mK.

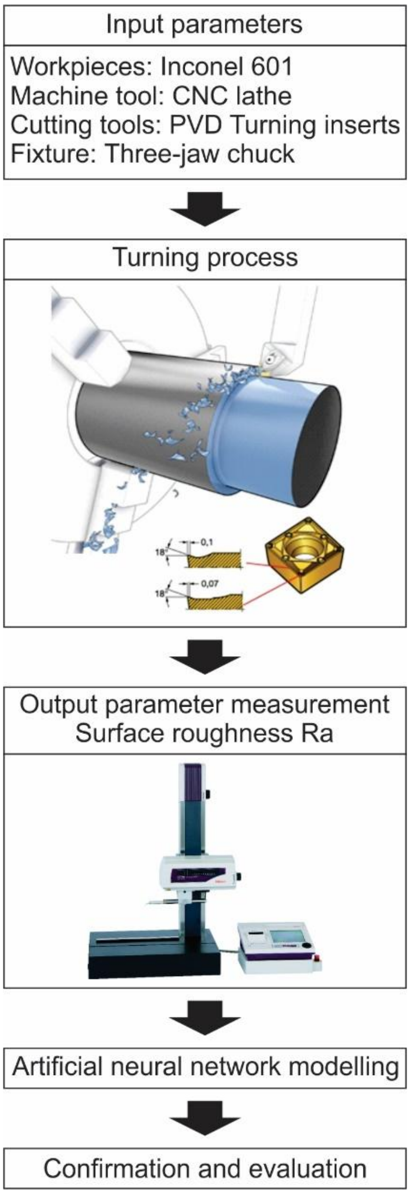

Fig. 1. Methodology.

Inconel 601 was used as the workpiece material. The workpiece was 40 mm in diameter and 400 mm long. Finish turning operations were performed on a CNC Turning Center (Mori Seiki Ecoline). Square-shaped turning inserts were used for all experiments. Additional information on the geometry and on the mechanical properties of the turning inserts are listed in Table 1. The turning inserts were clamped in a standard toolholder with an approach angle of 45°.

During experimental research, corner radius r (mm), feed f (mm/rev), depth of cut a_p (mm) and cutting speed v_c (m/min) were selected as input variables. Levels of input variables are shown in Table 2.

Table 1. Properties of the turning inserts.

Operation type	Finishing
Insert mounting style code	3
Fixing hole diameter	4.4 mm
Insert size and shape	CC09T3
Insert thickness	4 mm
Cutting edge count	2
Inscribed circle diameter	9.5 mm
Insert shape code	C
Cutting edge effective length	9.5 mm
Clearance angle major	7 °
Major cutting edge angle	95 °
Substrate	HC
Coating	PVD TiAlN+TiAlN

Table 2. Levels of input variables

Parameters	Levels		
	Minimum	Medium	Maximum
r (mm)	0.2	0.4	0.8
f (mm/rev)	0.05	0.1	0.15
a_p (mm)	1.2	1.4	1.6
v_c (m/min)	50	55	60

The surface roughness (Ra) measurements were done on a Mitutoyo Surftest SV device with the following basic characteristics: measuring speed 0.05 mm/s, stylus tip angle 60° and stylus tip radius 2 μm. The parameter Ra was evaluated within the evaluation length, which consists of five sampling lengths. The sampling length corresponds to the cut-off wavelength of the profile filter. Gaussian filter was used. The measurement was conducted with a cut-off length of 0.8 mm, a sampling length of 0.8 mm, and an evaluation length of 4 mm. Measurements were taken along the contour lines on the workpiece, in feed direction. All measurements were performed under controlled microclimatic conditions.

After experimental research and measurements, the ANN model was created. The ANN should predict the output parameters of the machining process based on input parameters.

Performance evaluation of the generated model was performed on bases of additional - confirmation experiments.

Assessment of the possibility of predicting output results using ANN model was performed based on percentage error (PE) and absolute error (AE), according to the equations:

$$PE = \left|\frac{Ra_p - Ra_m}{Ra_m}\right| \cdot 100\% \quad (1)$$

$$AE = \left|Ra_p - Ra_m\right| \quad (2)$$

where: Ra_p - surface roughness predicted value, Ra_m - surface roughness measured value.

Based on the obtained *PE* and *AE* results, the evaluation of assessments and evaluation of the possibility of application was performed, i.e. adequacy of ANN model and its application for prediction of surface roughness.

3. RESULTS

The experimental research was conducted according to a full factorial experiment. Given that all combinations of four input sizes at three levels were examined, a total of 81 experiments were conducted. Table 3 shows the results of measuring the surface roughness using the parameter *Ra*, which is most often measured in practice.

Table 3. Results.

No.	r (mm)	f (mm/rev)	a_p (mm)	v_c (m/min)	Ra_m (μm)	Ra_p (μm)	AE (μm)	PE (%)
1	0.2	0.05	1.2	50	0.625	0.634	0.009	1.392
2	0.4	0.05	1.2	50	0.313	0.315	0.002	0.551
3	0.8	0.05	1.2	50	0.156	0.148	0.008	5.318
4	0.2	0.1	1.2	50	2.504	2.497	0.007	0.279
5	0.4	0.1	1.2	50	1.253	1.252	0.001	0.101
6	0.8	0.1	1.2	50	0.626	0.622	0.004	0.616
7	0.2	0.15	1.2	50	5.625	5.629	0.004	0.077
8	0.4	0.15	1.2	50	2.813	2.811	0.002	0.065
9	0.8	0.15	1.2	50	1.406	1.416	0.010	0.707
10	0.2	0.05	1.4	50	0.638	0.642	0.004	0.676
11	0.4	0.05	1.4	50	0.319	0.323	0.004	1.274
12	0.8	0.05	1.4	50	0.159	0.156	0.003	2.134
13	0.2	0.1	1.4	50	2.552	2.550	0.002	0.097
14	0.4	0.1	1.4	50	1.275	1.279	0.004	0.324
15	0.8	0.1	1.4	50	0.638	0.636	0.002	0.358
16	0.2	0.15	1.4	50	5.738	5.740	0.002	0.028
17	0.4	0.15	1.4	50	2.869	2.867	0.002	0.069
18	0.8	0.15	1.4	50	1.434	1.438	0.004	0.309
19	0.2	0.05	1.6	50	0.652	0.652	0.000	0.005
20	0.4	0.05	1.6	50	0.325	0.330	0.005	1.656
21	0.8	0.05	1.6	50	0.163	0.164	0.001	0.350
22	0.2	0.1	1.6	50	2.604	2.602	0.002	0.081
23	0.4	0.1	1.6	50	1.308	1.305	0.003	0.227
24	0.8	0.1	1.6	50	0.656	0.650	0.006	0.964
25	0.2	0.15	1.6	50	5.853	5.848	0.005	0.088
26	0.4	0.15	1.6	50	2.925	2.921	0.004	0.146
27	0.8	0.15	1.6	50	1.463	1.461	0.002	0.163
28	0.2	0.05	1.2	55	0.643	0.632	0.011	1.734
29	0.4	0.05	1.2	55	0.321	0.311	0.010	3.206
30	0.8	0.05	1.2	55	0.161	0.147	0.014	8.596
31	0.2	0.1	1.2	55	2.571	2.569	0.002	0.094
32	0.4	0.1	1.2	55	1.286	1.277	0.009	0.697
33	0.8	0.1	1.2	55	0.643	0.634	0.009	1.331
34	0.2	0.15	1.2	55	5.786	5.800	0.014	0.245
35	0.4	0.15	1.2	55	2.893	2.894	0.001	0.028
36	0.8	0.15	1.2	55	1.446	1.449	0.003	0.218
37	0.2	0.05	1.4	55	0.655	0.645	0.010	1.584
38	0.4	0.05	1.4	55	0.328	0.322	0.006	1.976

39	0.8	0.05	1.4	55	0.164	0.165	0.001	0.656
40	0.2	0.1	1.4	55	2.621	2.621	0.000	0.001
41	0.4	0.1	1.4	55	1.311	1.303	0.008	0.584
42	0.8	0.1	1.4	55	0.655	0.656	0.001	0.112
43	0.2	0.15	1.4	55	5.898	5.908	0.010	0.167
44	0.4	0.15	1.4	55	2.949	2.948	0.001	0.050
45	0.8	0.15	1.4	55	1.475	1.473	0.002	0.123
46	0.2	0.05	1.6	55	0.668	0.663	0.005	0.822
47	0.4	0.05	1.6	55	0.334	0.336	0.002	0.659
48	0.8	0.05	1.6	55	0.167	0.182	0.015	9.122
49	0.2	0.1	1.6	55	2.671	2.677	0.006	0.220
50	0.4	0.1	1.6	55	1.336	1.333	0.003	0.260
51	0.8	0.1	1.6	55	0.668	0.681	0.013	1.974
52	0.2	0.15	1.6	55	6.011	6.018	0.007	0.122
53	0.4	0.15	1.6	55	3.005	3.003	0.002	0.083
54	0.8	0.15	1.6	55	1.503	1.502	0.001	0.097
55	0.2	0.05	1.2	60	0.667	0.667	0.000	0.056
56	0.4	0.05	1.2	60	0.339	0.335	0.004	1.172
57	0.8	0.05	1.2	60	0.167	0.165	0.002	1.462
58	0.2	0.1	1.2	60	2.667	2.667	0.000	0.015
59	0.4	0.1	1.2	60	1.337	1.335	0.002	0.141
60	0.8	0.1	1.2	60	0.667	0.677	0.010	1.446
61	0.2	0.15	1.2	60	6.008	5.999	0.009	0.150
62	0.4	0.15	1.2	60	3.004	3.003	0.001	0.027
63	0.8	0.15	1.2	60	1.511	1.506	0.005	0.334
64	0.2	0.05	1.4	60	0.679	0.681	0.002	0.279
65	0.4	0.05	1.4	60	0.340	0.342	0.002	0.443
66	0.8	0.05	1.4	60	0.170	0.173	0.003	1.849
67	0.2	0.1	1.4	60	2.717	2.723	0.006	0.223
68	0.4	0.1	1.4	60	1.358	1.361	0.003	0.222
69	0.8	0.1	1.4	60	0.679	0.692	0.013	1.951
70	0.2	0.15	1.4	60	6.113	6.110	0.003	0.049
71	0.4	0.15	1.4	60	3.056	3.056	0.000	0.010
72	0.8	0.15	1.4	60	1.528	1.528	0.000	0.024
73	0.2	0.05	1.6	60	0.692	0.697	0.005	0.778
74	0.4	0.05	1.6	60	0.346	0.347	0.001	0.297
75	0.8	0.05	1.6	60	0.173	0.182	0.009	5.158
76	0.2	0.1	1.6	60	2.767	2.782	0.015	0.554
77	0.4	0.1	1.6	60	1.388	1.386	0.002	0.119
78	0.8	0.1	1.6	60	0.692	0.708	0.016	2.321
79	0.2	0.15	1.6	60	6.225	6.223	0.002	0.025
80	0.4	0.15	1.6	60	3.113	3.108	0.005	0.171
81	0.8	0.15	1.6	60	1.556	1.551	0.005	0.320
						Minimum	0.000	0.001
						Maximum	0.016	9.122
						Mean	0.005	0.894

After conducting experiment and gathering data sets, the ANN model development is approached. ANN model for prediction is based on the feed – forward ANN with back propagation training algorithm. The proposed three-layer ANN architecture has four input parameters - corner radius, feed, depth of cut, cutting speed and one target parameter - surface roughness. The input data is on the format 4x81, and target data is on the format 1x81. The optimal number of hidden neurons can be determined using various rules, but obviously there is no general procedure to find an optimal ANN architecture, and the mentioned rules can serve only as a good guideline. For the purposes of this paper, optimal ANN architecture will be found based on the trial and error method. Development of ANN model is conducted in Matlab within artificial neural network toolbox through Fitting app, which is used for Input-Output and Curve Fitting tasks. Also, Matlab has apps for another type of tasks such as: Pattern Recognition and Classification, Clustering, and Dynamic Time Series. Data set for training consist of 81 samples which were randomly divided into three parts in proportion 70:15:15. The first part (57 samples) was used as an ANN training set, the second part (12 samples) as validation set, and the third part (12 samples) as the testing set. For all three dataset parts Mean Squared Error (*MSE*) values were calculated as performance measure. As a training algorithm Levenberg – Marquardt was used as a first choice for supervised learning (Figure 2).

Fig. 2. Training process of optimal architecture.

In this study numerous architectures were tested and, as an optimal solution, showed architecture with six neurons in hidden layer. The process of training, validation and testing of ANN model, regression and error histogram can be seen in Figure 3 and Figure 4, respectively. Based on the mentioned above, it can be seen that the developed ANN model is well trained, given the fact that correlation coefficient is R=0.99999, which is a measure of how well the variation in the output is explained by the targets. If this number is R=1, then there is a perfect correlation between targets and outputs. In our example, the number is very close to 1, which indicates a good fit.

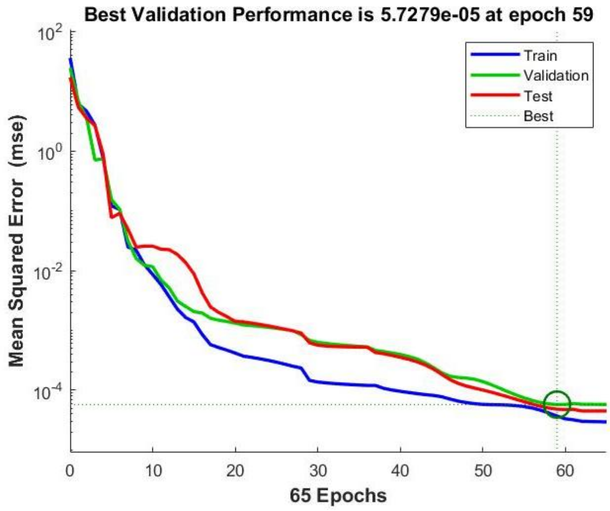

Fig. 3. Performance of optimal architecture

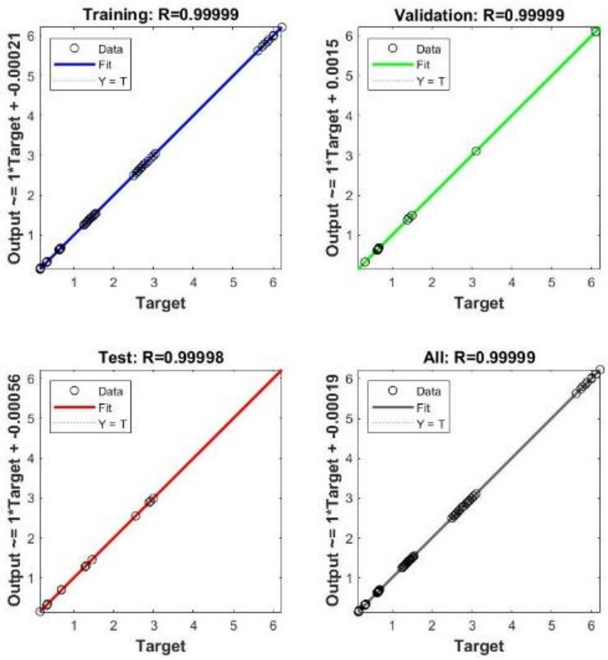

Fig. 4. Regression of optimal architecture.

The prediction results are shown together with the experimental results in Table 1. After that, *PE* and *AE* were calculated for each individual experiment (Table 1).

During the training experiments, the maximum absolute error is 0.016 μm, and the maximum percentage error is 9.122 %. The mean absolute error during the training experiments is 0.005 μm and the mean percentage error is 0.894 %.

The mean absolute error of the confirmation experiments is 0.012 μm and the mean percentage error is 1.303 %.

Additional validation of the obtained model was performed through additional 16 confirmation experiments (Table 4). Confirmation experiments were conducted for "unknown" machining parameters. The mean absolute error of the confirmation experiments is 0.012 μm and the mean percentage error is 1.303 %. A small percentage error, and especially a small average absolute error, additionally indicate the validity of the developed ANN model and the possibility of its practical implications in real turning processes.

Table 4. Confirmation results.

No.	*r* (mm)	*f* (mm/rev)	a_p (mm)	v_c (m/min)	Ra_m (μm)	Ra_p (μm)	*AE* (%)	*PE* (μm)
1	0.4	0.07	1.3	52	0.635	0.641	0.006	0.876
2	0.8	0.07	1.3	52	0.318	0.318	0.000	0.131
3	0.4	0.13	1.3	52	2.191	2.144	0.047	2.158
4	0.8	0.13	1.3	52	1.096	1.090	0.006	0.524
5	0.4	0.07	1.5	52	0.642	0.659	0.017	2.577
6	0.8	0.07	1.5	52	0.321	0.330	0.009	2.722
7	0.4	0.13	1.5	52	2.214	2.194	0.020	0.912
8	0.8	0.13	1.5	52	1.107	1.111	0.004	0.368
9	0.4	0.07	1.3	58	0.649	0.660	0.011	1.760
10	0.8	0.07	1.3	58	0.324	0.326	0.002	0.655
11	0.4	0.13	1.3	58	2.238	2.230	0.008	0.340
12	0.8	0.13	1.3	58	1.119	1.125	0.006	0.504
13	0.4	0.07	1.5	58	0.655	0.674	0.019	2.854
14	0.8	0.07	1.5	58	0.328	0.338	0.010	2.940
15	0.4	0.13	1.5	58	2.261	2.270	0.009	0.404
16	0.8	0.13	1.5	58	1.132	1.145	0.013	1.132
						Minimum	0.000	0.131
						Maximum	0.047	2.940
						Mean	0.012	1.303

4. CONCLUSION

In this research, an ANN model was developed and proposed that models the conditions under which the experimental studies of turning process of Inconel 601 were performed. The model establishes a cause-and-effect relationship between the input variables (processing parameters and the geometry of the cutting tool), and surface roughness of the machined surface as an output variable.

With an adequate selection of input variables, the mean arithmetic roughness of the surface in the range of 0.156 μm to 6.225 μm can be obtained by turning process. The obtained surface roughness values indicate the possibility of controlling the quality of the machined surface in a very wide range. This is very important considering that the goal is not to get the highest possible quality of the machined surface, but the required level (required by the technical documentation). The minimum value of *Ra* indicates the possibility of obtaining extremely high qualities of the machined surface, which avoids subsequent finishing operations, which also contributes to the reduction of processing time and processing costs.

The developed ANN model provides modeling of the final turning process, as well as the selection of input variables with which a certain surface roughness will be achieved with acceptable prediction errors. The obtained percentage and absolute errors indicate the possibility of practical application of the developed network. Namely, the maximum *PE* values during training and confirmation experiments were 9,122% and 2,940%, respectively. Furthermore, the maximum *AE* values during training and confirmation experiments were 0.016 μm and 0.047 μm, respectively. *AE* quantifies the real deviations of the required value of *Ra*, in relation to the obtained value of *Ra*. Absolute deviations of the order of several tenths of a micrometer, and in most cases even smaller, can be considered acceptable from a practical point of view.

Future research will be focused on the consideration of including a larger number of input and output variables from the turning process, and the optimization of the selection of machining parameters, geometrical characteristics of cutting inserts, as well as the consideration of a larger number of typical interventions in turning processing.

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