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Analysis of Grain Size Effect of Titanium Ti-6Al-4V Depending on Surface Roughness at Different Cutting Parameters Using Artificial Intelligence Methods

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Abstract

The article presents the results of a study of the effect of cutting modes of Ti-6Al-4V alloy with different grain size, including in the ultrafine-grained state obtained by severe plastic deformation, on the roughness of the machined surface using a neural network model. A neural network model has been developed that predicts the surface roughness of titanium alloy during cutting depending on the grain size and processing modes (speed, feed per revolution, and cutting depth). To form a data set of sufficient power for training neural networks, a data augmentation method was used, for which an auxiliary regression model was built. To select the most rational network architecture, a random search in the hyperparameter space was used. Testing the developed neural network model on actual data showed an error not exceeding 8.7% according to mean absolute percentage error.

Keywords: Titanium alloy; Cutting modes; Roughness; Neural network; Deep learning

1. INTRODUCTION

The machining of titanium alloys by cutting causes significant problems due to the low durability of cutting tools, low cutting speeds, and difficulties in ensuring the required roughness of the machined surfaces of parts. This is due to the fact that most titanium alloys are high-strength, difficult-to-machine materials containing various hard carbides, aluminitrides, and high-strength phases in their structure, which cause increased wear of cutting tools [1]. The development of new high-strength alloys only exacerbates this problem, so finding ways to solve them is relevant in various branches of mechanical engineering [2–7]. In recent years, researchers have paid special attention to the development of nanostructured and ultrafine-grained (UFG) metals and alloys obtained by severe plastic deformation (SPD) methods [8,9]. In particular, UFG titanium alloys have a noticeable advantage over industrial coarse-grained alloys in strength and fatigue resistance [10]. In modern aircraft engine manufacturing, where titanium alloys are widely used primarily for manufacturing critical parts of gas turbine engines (disks, bushings, shafts, blades, etc.), manufacturing highly loaded parts from UFG titanium alloys will increase the strength, reliability, and durability of the product. Therefore, it is necessary to pay special attention to the choice of turning parameters when manufacturing parts from UFG alloys in order to obtain the required surface quality indicators.

One of the important criteria of surface quality is its roughness, which is an indicator of the integrity of the treated surface and quantitatively characterizes the microscopic roughness [11]. High surface roughness can easily lead to the development of small cracks and stress concentrators, which reduces the performance of titanium billets. Therefore, surface roughness control is an important task

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when turning or grinding. Researchers have carefully studied the surface integrity of complex surface treatment of titanium alloys. For example, in Ref. [12], a multi-criteria method for optimizing process parameters was proposed to reduce surface roughness and improve the material removal rate. In Ref. [13], the effect of grinding parameters such as cutting speed, feed rate, grinding depth and abrasive size on surface integrity was studied experimentally.

Obviously, the choice of rational cutting modes for new materials requires a large amount of experimental research to ensure the specified quality of the treated surface of the part. One of the tools that allows reducing the volume of experimental research, optimizing financial and time costs are methods of statistical processing and mathematical modeling. Methods of artificial intelligence, including methods of machine learning of neural network (NN) mathematical models, have been an actively developing area of digitalization of science and industry in recent years.

The objective of this work is to evaluate the potential for predicting the surface roughness of titanium alloys with different grain sizes using a NN model when selecting rational cutting modes. Due to the fact that the amount of experimental data was insufficient for training NNs, the method of augmentation of the training set using regression analysis of the data was used. For this purpose, auxiliary models obtained by planning multifactorial experiments with statistical processing and regression analysis were used. To achieve this goal, the following was done:

1. Statistical processing of experimental data and formation of an augmented training set for NN modeling of the cutting process.
2. Selection of the best neural network architecture for constructing a NN approximator that establishes the dependence of surface roughness on cutting modes, taking into account the grain size of the processed material.
3. Analysis of results and verification of the adequacy of the NN model.
4. Development of an algorithm for using the NN model in substantiating rational cutting modes for titanium alloys, which allows increasing the efficiency of the cutting process by reducing the processing time while ensuring the specified quality characteristics of the processed surface.

2. MATERIALS AND PROCESSING MODES

2.1. Materials

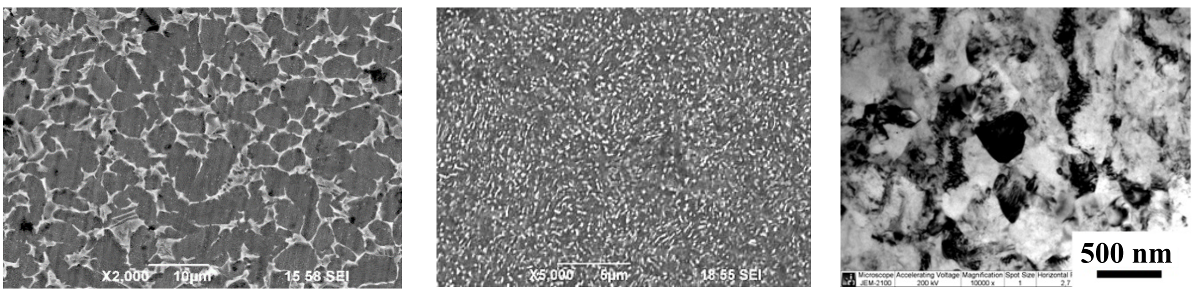
The material of this study was Grade 5 titanium alloy, according to the ASTM B348 standard. The as-received microstructure of bars with diameter 40 and 20 mm characterized by an average grain size of 25 and 10 μm, respectively. The chemical composition of alloy: Al—6.6%; V—4.9%; Zr—0.02%; Si—0.033%; Fe—0.18%; C—0.007%; O_2—0.17%; N_2—0.01%; H_2—0.002%; and titanium as the balance. To produce a Ti-6Al-4V alloy bar 20 mm in diameter with an UFG structure (grain size less than ~ 1.0 μm), an initial bar was processed via equal-channel angular pressing (ECAP) in 4 passes. The Bc route (a sequence of 90-degree turns of the workpiece bar) of ECAP processing was applied. The intersection angle between the channels of an ECAP die-set was 120 degrees [14]. ECAP specimens had microstructure with grain size about 0.5 μm (Fig. 1).

Thus, for the experiment we had 3 types of samples with different grain sizes: 25 μm—coarse grain (CG), 10 μm—medium grain (MG) and 0.5 μm—UFG.

2.2. Cutting Regimes and Surface Roughness

The cutting experimental regimes for the Ti-6Al-4V bars with CG and UFG structures were selected based on the Sandvik company's catalog of cutting conditions [15]. The cutting regimes were determined via a combination of the main cutting parameters: speed V (m/min), depth t (mm), and feed rate S (mm/rev).

In order to measure the roughness of a surface, a MarSurf PS1 measuring device (Mahr GmbH, Esslingen, Germany) was used, which provides R_a, R_z, and $R_{\max}$ data. The maximum measurement range was 350 μm (from −200 μm to +150 μm). Surface roughness measurements were carried out over a length of five millimeters. Four



(a) (b) (c)

Fig. 1. The microstructure of MG (a) and ECAP specimens from Ti-6Al-4V alloy (b,c): (a,b) SEM-image; (c) TEM image.

measurements were taken on each "zone" in diametrically opposite places and one rotation of 90 degrees. The device used for measurement was a contact device.

The experimental data on cutting parameters and roughness values are summarized in Table 1 (see Section 4 below).

Based on experimental data, regression mathematical models were constructed:
for CG structure

$$R_a = -4.218 + 0.103V + 27.119S + 8.403t - 0.610VS - 0.191Vt - 57.918St; \quad (1);$$

for MG structure

$$R_a = 0.620 + 0.015V + 8.780S + 0.190t - 0.143VS - 0.005Vt - 17.260St; \quad (2)$$

for UFG structure

$$R_a = 0.014 - 0.004V + 1.252S + 2.114t + 0.123VS - 0.021Vt - 6.740St. \quad (3)$$

The average error using the mean absolute percentage error (MAPE) metric of the constructed models does not exceed 2.5%, which allows them to be used in further studies.

3. DEVELOPMENT OF A NN MODEL

The obtained experimental data are insufficient for training such NN. So the method of augmenting the training set based on regression models (1)–(3) was applied [16]. Two parameters were fixed in the regression equations for augmentation and the dependences of R_a on the third parameter (with a constant step) were found. The obtained data were entered into the database. The parameters V, S, t varied in the ranges in which the experiments were conducted. The results, presented in graphical form, can be seen in Fig. 2.

Thus, 3,000 examples were obtained, which were subsequently used to train NN models. Of the 3,000 examples, 80% were used to train the models, 20% were used as a validation data set. Testing of the final best model was carried out on experimental data (24 examples).

To build a NN approximator for a group of titanium alloys, it is proposed to use the MLP NN [5]. The vector $\{M, V, S, t\}$ is specified as the network input, and R_a is specified as the output. Here M is the approximate grain size: 0.5 μm for UFG, 10 μm for MG, and 25 μm for CG. The NN was trained taking into account the recommendations given in Refs. [17–20]. After a random search in the space of various NN hyperparameters (number of layers, number of neurons, choice of activation function, training step), the best architecture with 5 hidden layers was selected. The *relu* activation function was used in each hidden layer, the training step was 0.0005. After finding the best model, it was retrained for 500 epochs. The results are shown in Fig. 3. The graphs show that the training was successful.

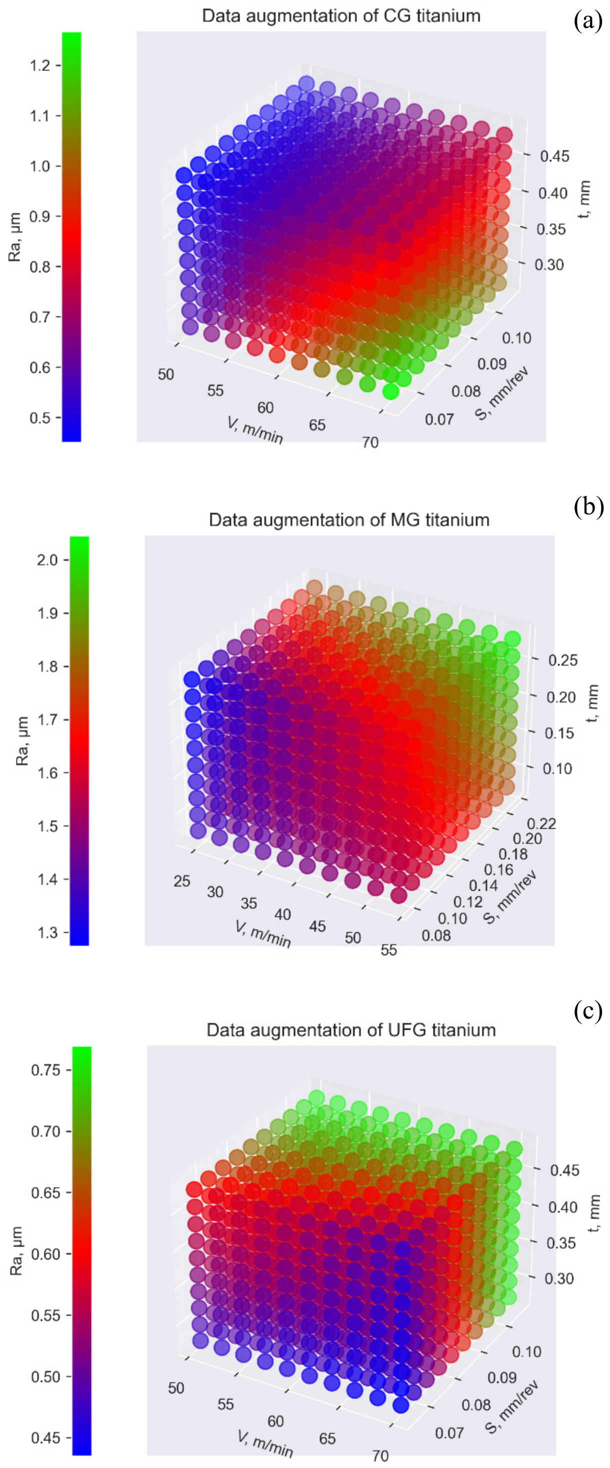


Fig. 2. Data obtained using augmentation with linear regression models for CG titanium (a), MG titanium (b) and UFG titanium (c).

The following results were obtained on the validation data: mean average error is 0.0026 μm (0.29% MAPE), mean square error is 1.44e–05. It is evident that the trained network qualitatively approximates the initial dependencies, which was expected. Note that the excellent results

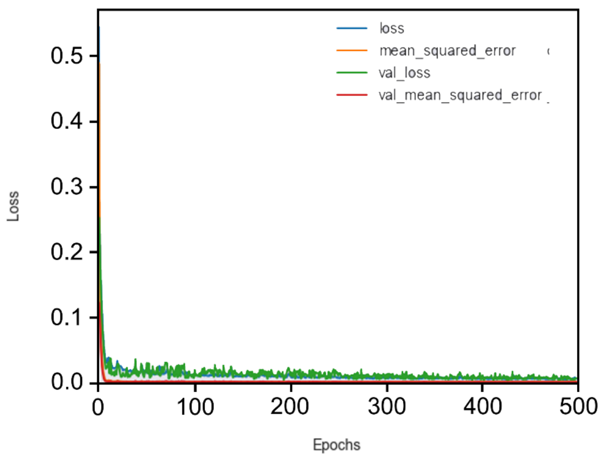


Fig. 3. Neural network training graphs for initial data normalization.

of validation data are explained by collecting them from the same distribution as the training data.

4. APPLICATION OF A NN MODEL

A comparison of roughness value predictions of the NN model with experimental data was carried out (Table 1).

The NN copes well with predicting roughness values for UFG and CG materials, but for MG alloy the discrepancies at two points (in experiments No. 17 and 21) become more noticeable. This can be because the experimental data for MG material were obtained in a fairly wide range.

Using this NN, we can obtain roughness dependencies on grain size for various processing parameters (Fig. 4).

The roughness dependence on grain size changes slightly when the cutting depth changes within the studied limits (Fig. 4a). In the UFG and MG regions the roughness dependence on grain size changes significantly when varying the feed rate: as S increases, so does the roughness (Fig. 4b). Moreover, at $S = 0.062$ mm/rev and at grain sizes up to 4.5 μm, the roughness remains virtually unchanged, which cannot be said at $S = 0.104$ mm/rev. There are virtually no qualitative differences in the CG region. Fig. 4c shows that the dependence of roughness on grain size with a change in cutting speed changes mainly only in the CG and MG regions. In the UFG region such changes are practically absent.

For greater clarity, the dependences of roughness on various cutting parameters were analyzed at some fixed grain sizes of titanium alloys (Fig. 5).

Based on the nature of the obtained dependencies of surface roughness on cutting modes and grain size, it was noted that MG material has a higher viscosity compared to

Table 1. Comparison of roughness obtained by the NN with experimental data for given input parameters.

No.	Grain size, [μm]	V, [m/min]	S, [mm/rev]	t, [mm]	R_a-experiment, [μm]	R_a-prediction, [μm]	Difference, [μm]
0	0.50	48	0.06	0.25	0.424	0.451	0.027
1	0.50	48	0.06	0.50	0.612	0.562	0.050
2	0.50	48	0.11	0.25	0.707	0.88	0.173
3	0.50	48	0.11	0.50	0.790	0.781	0.009
4	0.50	72	0.06	0.25	0.390	0.404	0.014
5	0.50	72	0.06	0.50	0.434	0.458	0.025
6	0.50	72	0.11	0.25	0.800	0.786	0.015
7	0.50	72	0.11	0.50	0.780	0.766	0.013
8	25.00	48	0.06	0.25	0.511	0.568	0.058
9	25.00	48	0.06	0.50	0.406	0.441	0.034
10	25.00	48	0.11	0.25	0.48	0.534	0.054
11	25.00	48	0.11	0.50	0.450	0.471	0.021
12	25.00	72	0.06	0.25	1.445	1.330	0.114
13	25.00	72	0.06	0.50	0.672	0.685	0.013
14	25.00	72	0.11	0.25	1.080	1.086	0.006
15	25.00	72	0.11	0.50	0.784	0.782	0.003
16	10.00	20.73	0.06	0.05	1.322	1.317	0.005
17	10.00	56.55	0.06	0.05	1.591	1.189	0.402
18	10.00	20.73	0.23	0.05	2.187	2.108	0.079
19	10.00	56.55	0.23	0.05	1.720	1.756	0.036
20	10.00	20.73	0.06	0.30	1.099	1.277	0.178
21	10.00	56.55	0.06	0.30	1.563	0.682	0.881
22	10.00	20.73	0.23	0.30	1.734	1.771	0.037
23	10.00	56.55	0.23	0.30	2.143	2.102	0.041

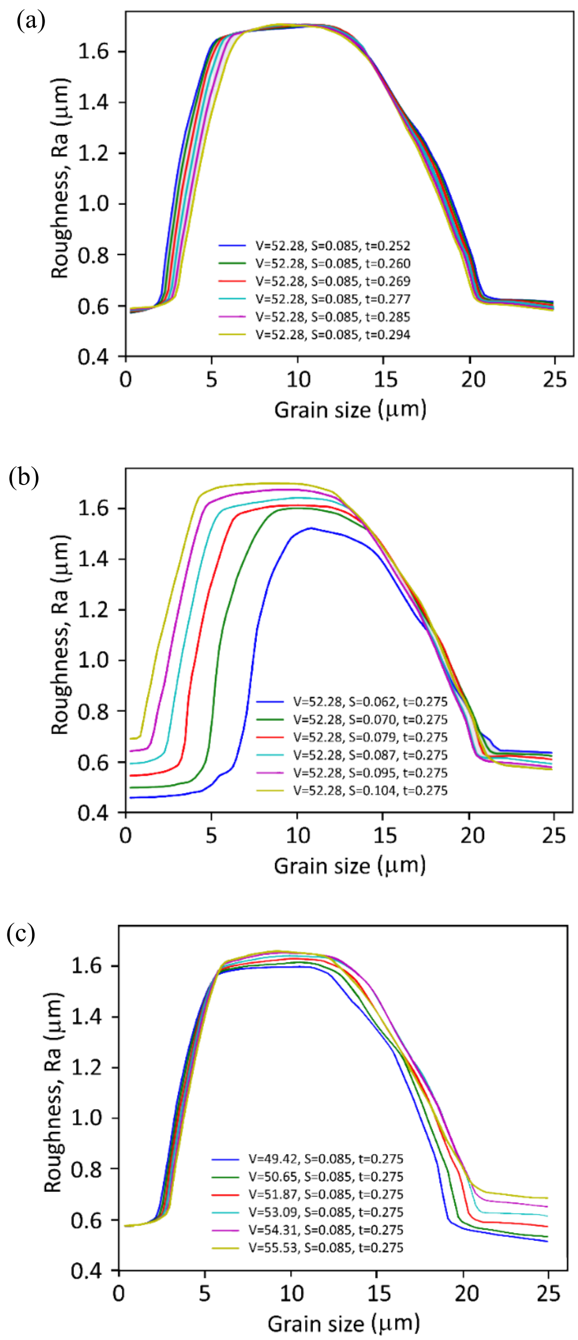


Fig. 4. Prediction of roughness in dependence on grain size with fixed turning parameters (a) V, S, (b) V, t, and (c) S, t.

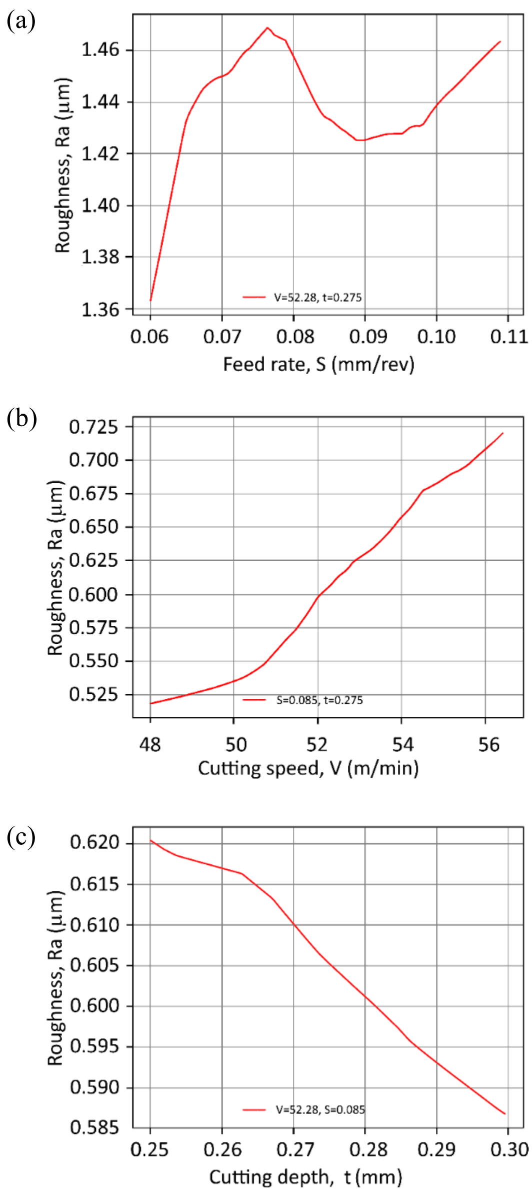


Fig. 5. Dependence of roughness on (a) feed rate at fixed V, t and grain size 15 µm; (b) on cutting speed at fixed S, t and grain size 24 µm (c) on cutting depth at fixed V, S with grain size of 24 µm based on NN predictions.

samples of the UFG and CG alloys, therefore, the roughness after its processing increases. To control the roughness of the UFG alloy, it is best to vary the feed rate, and for titanium materials with coarse and medium grain, it is better to use the cutting speed parameter.

5. CONCLUSION

Based on experimental roughness data of Ti-6Al-4V alloy with different grain sizes, a NN model was built to predict the surface after machining, depending on the grain size and processing modes (cutting speed, feed rate per revolution, cutting depth). Testing the NN model on actual data showed an error of no more than 8.7% according to the MAPE metric. The results of this work can be used as practical recommendations when machining titanium alloys with different grain sizes. In addition, the obtained NN approximators can become the basis for creating an adaptive control system for the cutting process of titanium alloys on CNC machines.

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Анализ влияния размера зерна титана Ti-6Al-4V на шероховатость поверхности при различных параметрах резания с использованием методов искусственного интеллекта

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Аннотация. В статье представлены результаты исследования влияния режимов резания сплава Ti-6Al-4V с различным размером зерна, в том числе в ультрамелкозернистом состоянии, полученном методом интенсивной пластической деформации, на шероховатость обработанной поверхности с использованием нейросетевой модели. Разработана нейросетевая модель, прогнозирующая шероховатость поверхности титанового сплава при резании в зависимости от размера зерна и режимов обработки (скорость, подача на оборот и глубина резания). Для формирования набора данных достаточной мощности для обучения нейронных сетей использован метод аугментации данных, для чего построена вспомогательная регрессионная модель. Для выбора наиболее рациональной архитектуры сети использован случайный поиск в пространстве гиперпараметров. Тестирование разработанной нейросетевой модели на фактических данных показало погрешность, не превышающую 8,7% по данным средней абсолютной процентной погрешности.

Ключевые слова: титановый сплав; режимы резания; шероховатость; нейронная сеть; глубокое обучение