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USE OF ARTIFICIAL NEURAL NETWORKS IN BALL BURNISHING PROCESS FOR THE PREDICTION OF SURFACE ROUGHNESS OF AA 7075 ALUMINUM ALLOY

UPORABA UMETNIH NEVRONSKIH MREŽ ZA NAPOVED HRAPAVOSTI POVRŠINE PRI KROGELNEM GLAJENJU ALUMINIJEVE ZLITINE AA 7075

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Burnishing is a plastic deformation process, and it has become more popular as a finishing process. Thus, it is especially crucial to select the burnishing parameters to reduce the surface roughness. In the present study, a surface roughness prediction model using artificial neural network (ANN) is developed to investigate the effects of burnishing conditions during machining of AA 7075 aluminum material. The ANN model of surface roughness parameters (R_a) is developed considering the conditions as burnishing force, number of tool passes, feed rate and burnishing speed. The experimental results were trained in an ANN program and the results were compared with experimental values. It is observed that the experimental results coincided with ANN results.

Keywords: Ball burnishing, surface roughness, modeling, artificial neural network

Glajenje je proces plastične deformacije in je postalo zelo razširjeno kot končna obdelava. Za zmanjšanje hrapavosti površine je zelo je pomembna izbira parametrov glajenja.V tej raziskavi je bil z uporabo nevronske mreže (ANN) razvit model glajenja pri obdelavi aluminijeve zlitine AA 7075. Model parametra hrapavosti površine (R_a) je bil razvit z upoštevanjem pogojev: polirna sila, število prehodov orodja, hitrost podajanja in hitrost poliranja. Eksperimentalni podatki so uporabljeni za ANN-program, rezultati modela pa primerjani z eksperimentalnimi. Rezultati ANN se dobro ujemajo z eksperimentalnimi.

Ključne besede: krogelno glajenje, hrapavost površine, modeliranje, umetna nevronska mreža

1 INTRODUCTION

The surface quality is an important parameter to evaluate the productivity of machine tools as well as machined components. Hence, achieving the desired surface quality is of great importance for the functional behavior of mechanical parts [1]. Surface roughness is used as the critical quality indicator for the machined surfaces and since, it affects several properties such as wear resistance, fatigue strength, coefficient of friction, lubrication, wear rate and corrosion resistance of the machined parts [2]. In today's manufacturing industry, special attention is given to dimensional accuracy and surface finish. Thus, measuring and characterizing the surface finish can be considered as a predictor for the machining performance.

Burnishing is considered as a cold-working finishing process differing from other cold-working surface treatment processes such as shot peening and sand blasting, etc. in that it produces a good surface finish and also induces residual compressive stresses at the metallic surface layers [3,4]. Accordingly, the burnishing is distinguished from chip-forming finishing processes such as grinding, honing, lapping and super-finishing which induce residual tensile stresses at the machined surface layers [5]. Also, burnishing is economically desirable, because it is a simple and cheap process, requiring less time and skill to obtain a high-quality surface finish [6]. The burnishing process can be achieved by applying a highly polished and hard ball or roller onto a metallic surface under pressure. As indicated in **Figure 1**, pressure causes the peaks of the metallic surface to spread out permanently and fill the valleys [4], when the applied burnishing pressure exceeds the yield strength of the metallic material.

The surface of the metallic material will be smoothed out and because of the plastic deformation the surface is

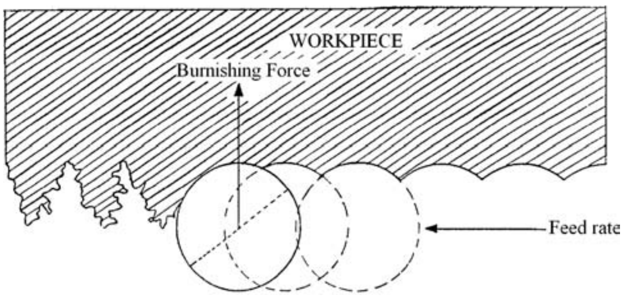

Figure 1: Schematic representation of ball burnishing process [7]
Slika 1: Shematska predstavitev procesa krogelnega poliranja [7]

work hardened and the material is left with a residual stress distribution compressive on the surface [4]. The changes in surface characteristics due to burnishing will cause improvements in surface hardness, wear resistance, fatigue resistance, yield and tensile strength and corrosion resistance, as claimed by many authors [8–11].

The aim of the present work was to investigate the effect of burnishing parameters such as burnishing force (*F*/N), number of tool passes (*N*), feed rate (*f*/(mm/min)) and burnishing speed (*v*/(r/min)) on the surface roughness (R_a/μm) of AA 7075 aluminum with the use of ANN.

2 MATERIAL AND EXPERIMENTAL PROCEDURE

2.1 Material

In this study, high strength precipitation hardening 7XXX series wrought aluminum alloy AA 7075 was used. The strength and good mechanical properties make the AA 7075 aluminum alloy appropriatefor use in aerospace industry. The chemical composition and mechanical properties of the workpiece material is given in **Table 1**.

Table 1: Chemical and mechanical properties of workpiece material
Tabela 1: Sestava in mehanske značilnosti obdelovanca

Chemical composition *w*/%	Al	Cu	Mg	Cr	Zn
	90.0	1.60	2.50	0.23	5.60
Mechanical properties	Tensile strength (MPa)	Yield strength (MPa)	Shear strength (MPa)	Fatique strength (MPa)	Hardness (HB 500)
	220	95	150	160	60

The three part workpiece material shown in **Figure 2**, was prepared with the dimensions of 30 mm diameter and 60 mm in length with each segment with 20 mm in length.

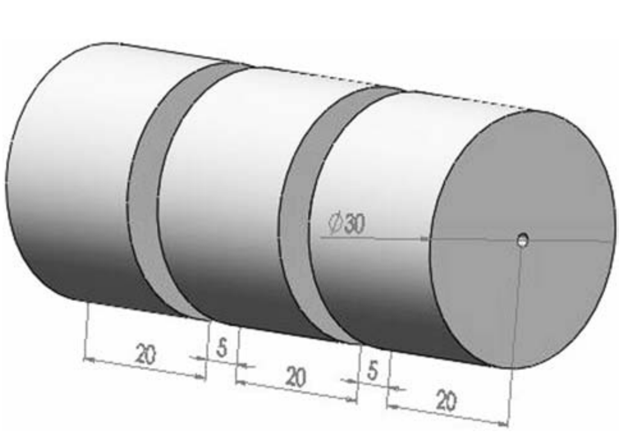

Figure 2: Dimensions of workpiece material
Slika 2: Mere obdelovanca

2.2 Machines and Equipments

A 18 mm diameter steel ball was used for burnishing. The detailed drawing is shown in **Figure 3**. When the ball or roller is pressed against the surface of the metallic specimen, a pre-calibrated spring was compressed used mainly to reduce the possible sticking of the tool onto the surface.

The experiments were performed on a FANUC GT-250B CNC machining center. The burnishing tool was mounted on the CNC turret as shown in **Figure 4**.

Dry turning and burnishing were used in all the experimental work and alcohol was used to clean the specimens before burnishing. The cleaning of the ball was carried out continuously in order to prevent any hard particles from entering the contact surface between the tool and the specimen, such hard particles usually leaving deep scratches that may damage the burnished surface of the specimen. The Phynix TR-100 model surface roughness tester was used to measure the surface roughness of the burnished samples. Cut off length was chosen as 0.3 for each roughness measurement. Six measurements of surface roughness were taken from the samples and average of the roughness was used in modeling.

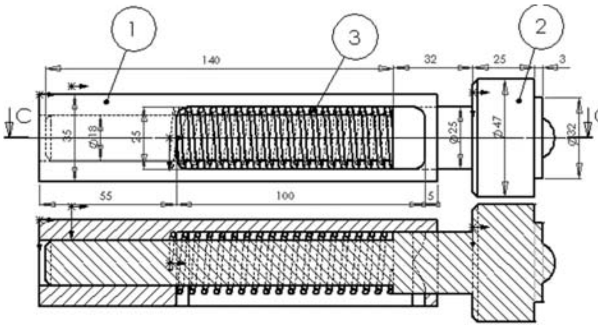

Figure 3: Detailed drawing of the ball burnishing tool: (1) casing; (2) adapter cover; (3) spring
Slika 3: Načrt orodja za krogelno glajenja. (1) ohišje, (2) prilagoditveni pokrov, (3) vzmet

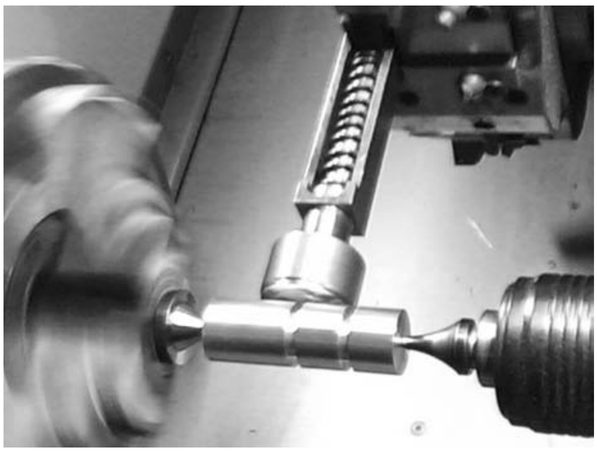

Figure 4: Ball burnishing experimental set up
Slika 4: Eksperimentalna priprava za krogelno glajenje

3 MODELING WITH ARTIFICIAL NEURAL NETWORK (ANN)

Computers are an integral part of day to day activities in engineering design and engineers have utilized various applications to assist them improve their design [12]. ANN mimics some basic aspects of the brain functions [13–15]. It is based on the neural structure of the human brain, which processes information by means of interaction between many neurons [13,16]. In the past few years there has been a constant increase in interest of neural network modeling in different fields of materials science. The basic unit in the ANN is the neuron. The neurons are connected to each other with weight factor. A network is usually trained using a large number of input with corresponding output data [17].

The ANN architecture used modeling of surface roughness is illustrated in **Figure 5**. It consists of many simple processing neurons organized in a sequence of layers: input, intermediate (hidden) and output layers. The simulation problem consists of finding a satisfactory relationship between a set of neurons representing the input data and associated known output. The selection of the input parameters is a very important aspect of neural network modeling [17]. All relevant input parameters must be represented as the input data of the neural network. In this study burnishing force, number of passes, feed and burnishing speed were used as inputs while surface roughness was used as an output.

The ANN model used is 4 : 5 : 5 : 1 multilayer architecture as shown in **Figure 5**. Y_j (j = 1, 2,..,5) and Y_i (i = 1, 2,..,5) are the output of the hidden neurons.

3.1 The Training of the Network

Generally, there are three different learning strategies. First, the trainer may tell the network what it should learn (Supervised Learning), second, the trainer may indicate whether or not the output is correct without telling what the network should learn (Reinforcement Learning) and finally, the network learns without any intervention of the trainer (Unsupervised Learning). The learning set consists of the inputs and the outputs used in training the network. The required outputs take place in this set in the case of supervised learning, while in other cases, they are not found in it [17,18]. In the present study, the supervised learning approach was used. The computer program has been developed under MATLAB [19] and as given in **Table 2**, a database of 30 experimental results was used to train the ANN model.

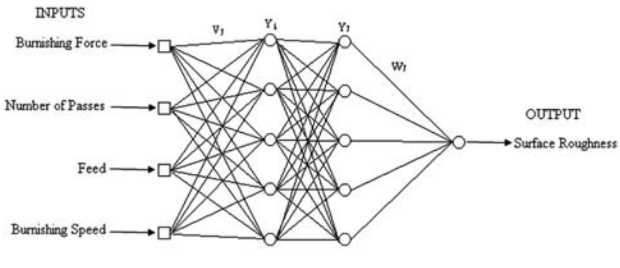

Figure 5: The constructed ANN model
Slika 5: Razviti ANN-model

Table 2: Experimental results and training set of ANN modeling
Tabela 2: Eksperimentalni rezultati in učni podatki za ANN-modeliranje

Exp.no	Burnishing force F/(9,86 N)	Number of passes N	Feed rate f/(mm/min)	Burnishing speed v/(r/min)	Measured surface roughness R_a/μm
1	9	2	0.62	200	0.30
2	10	3	0.80	400	0.37
3	11	2	0.60	500	0.37
4	12	3	0.45	800	0.47
5	13	2	0.45	1000	0.44
6	14	4	0.45	600	0.65
7	15	4	0.45	600	0.71
8	16	2	0.27	200	0.60
9	17	3	0.62	600	0.69
10	18	4	0.45	600	0.89
11	19	3	0.27	400	0.85
12	20	2	0.27	500	0.78
13	21	3	0.45	600	0.91
14	22	4	0.27	1000	1.12
15	23	2	0.62	700	0.75
16	24	3	0.45	600	1.06
17	25	2	0.27	200	1.02
18	9	4	0.27	200	0.38
19	10	2	0.62	300	0.33
20	12	4	0.45	400	0.54
21	16	3	0.80	500	0.63
22	13	3	0.60	600	0.51
23	15	2	0.27	700	0.55
24	16	3	0.62	800	0.64
25	17	4	0.45	900	0.82
26	20	3	0.62	1000	0.81
27	14	2	0.45	400	0.49
28	16	4	0.80	600	0.76
29	11	3	0.27	800	0.42
30	10	2	0.45	800	0.33

3.2 Testing Stage

In order to understand whether an ANN is making good predictions, test data that has never been presented to the network are used and the results are checked at this stage. The statistical methods of root mean square error (RMSE), the coefficient of multiple determination (R^2) values have been used for making comparisons [17,20–23]. These values are determined by the following equations:

$$RMSE = \left(\frac{1}{n} \sum_j \left| a_j - p_j \right|^2 \right)^{1/2} \tag{1}$$

$$R^2 = 1 - \left(\frac{\sum_j \left(a_j - p_j \right)^2}{\sum_j \left(p_j \right)^2} \right) \tag{2}$$

Table 3: Validation set used for ANN analysis
Tabela 3: Podatki za preverjanje ANN-analize

Exp.no	Burnishing force F/(9,81 N)	Number of passes N	Feed rate f/(mm/min)	Burnishing speed v/(r/min)	Measured surface roughness R_a/µm	*ANN*			
						Predicted surface roughness R_{ap}/µm	Error %	*RMSE*	R^2
1	10	2	0.62	200	0.34	0.36	-6.75	0.0051	0.9960
2	10	3	0.80	600	0.36	0.38	-4.23	0.0034	0.9984
3	11	4	0.27	200	0.50	0.52	-4.42	0.0049	0.9982
4	12	3	0.45	400	0.47	0.45	5.22	0.0055	0.9970
5	13	3	0.45	1000	0.49	0.48	1.91	0.0021	0.9996
6	15	3	0.10	600	0.64	0.63	2.22	0.0032	0.9995
7	17	4	0.27	600	0.84	0.87	-3.46	0.0065	0.9989
8	18	4	0.27	800	0.89	0.91	-2.12	0.0042	0.9996
9	21	2	0.62	800	0.72	0.74	-3.25	0.0052	0.9990
10	22	3	0.45	600	0.96	0.96	0.50	0.0011	1.0000
11	23	2	0.27	300	0.92	0.91	1.36	0.0028	0.9998
12	24	4	0.62	200	1.09	1.04	4.59	0.0112	0.9977
13	25	2	0.80	1000	0.87	0.89	-2.29	0.0045	0.9995
14	10	3	0.62	900	0.37	0.39	-4.64	0.0038	0.9980
15	11	4	0.45	800	0.47	0.48	-1.72	0.0018	0.9997
16	12	2	0.80	300	0.39	0.38	1.57	0.0014	0.9997
17	13	3	0.80	600	0.46	0.45	2.94	0.0030	0.9991
18	14	4	0.60	700	0.64	0.63	1.88	0.0027	0.9996
19	9	2	0.27	800	0.37	0.38	-2.38	0.0020	0.9995
20	25	4	0.27	1000	1.16	1.06	8.62	0.0224	0.9911
						Average error: 3.30% *Average RMSE: 0.0048* *Average R^2: 0.998*			

where; p is the predicted value, a the actual value and n the number of samples.

4 RESULTS AND DISCUSSION

The comparisons of experimental results with the ANN predictions have been depicted in terms of percentage error for validation set of experiments. From **Table 3** it is evident that for our set of data the neural network predicts the surface roughness nearer to the experimental values. In the prediction of surface roughness values the average errors for ANN is found to be as 3.30 %.

The average *RMSE* was found to be as 0.0048. The value of the multiple coefficient of R^2 between experimental results and ANN prediction is obtained as 0.998. This value showed that ANN model fits well with

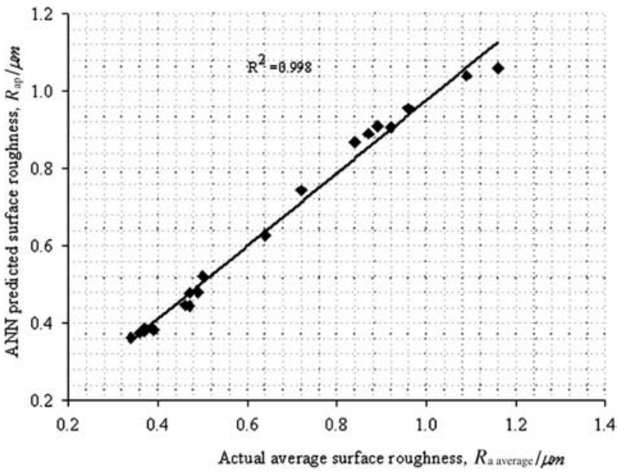

Figure 6: Actual average surface roughness against ANN prediction
Slika 6: Dejanska hrapavost proti ANN-napovedi

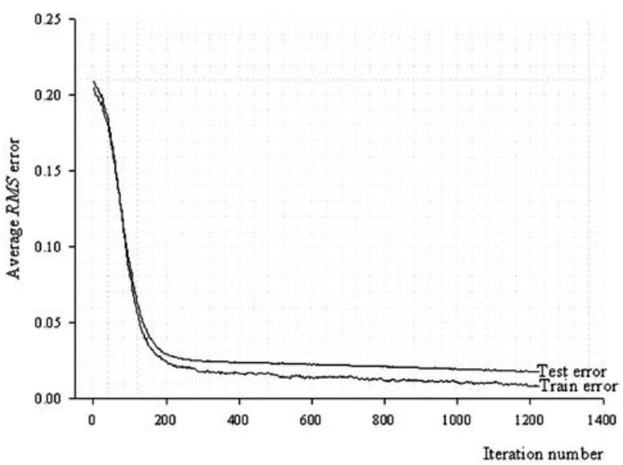

Figure 7: Learning behavior of ANN model
Slika 7: Učno vedenje ANN-modela

the experimental results. **Figure 6** illustrates the ANN predictions against the experimental results.

The training of the neural network was performed with an allowable error of 0.01 (sum of squared error over the output neurons). The learning behavior of this particular network is shown in **Figure 7**.

5 CONCLUSION

In this study, for the modeling of the effects of ball burnishing parameters (burnishing force, number of passes, feed rate and burnishing speed) on the surface roughness of the AA 7075 aluminum alloy depending on various processing parameters, an ANN-based approach has been suggested and successfully implemented. As **Figure 6** indicates for each average surface roughness value the predictions of the ANN are very close to the experimental results. It may be concluded that the ANN may be used as a good alternative for the analysis of the effects of burnishing parameters on the average surface roughness. In the field of surface roughness, ANNs are good alternative to conventional empirical modeling. The advantages of the ANN compared to classical methods are speed, simplicity and capacity to learn from the experimental results and also none need for a wider experimental study. Because of this fact that, engineering effort may be reduced in the areas where ANN modeling is preferred.

In this study the focus was to predict the average surface roughness in ball burnishing process. The results from ANN model will allow to improve determination of the average surface roughness value and help to determine in a short time the behavior of the experimental results.

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