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Predictive Modelling of Ball Burnishing Process Using Regression Analysis and Neural Network

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The present paper focuses on two techniques, namely regression and neural network techniques, for predicting surface roughness in ball burnishing process. Values of surface roughness predicted by the two techniques were compared with experimental values. Also, the effects of the main burnishing parameters on surface roughness have been determined. Surface roughness (R_a) was taken as response (output) variable and burnishing force, number of passes, feed rate, and burnishing speed were taken as input parameters. Relationship between the surface roughness and burnishing parameters was found out for direct measurement of the surface roughness. Results showed the application of the regression and neural network models to accurately predict the surface roughness.

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 which good surface finish is produced and also residual compressive stresses at the metallic surface layers are induced [1, 2]. Accordingly, burnishing distinguishes itself from chip-forming finishing processes such as grinding, honing, lapping, and super-finishing, which induce residual tensile stresses at the machined surface layers [1-4]. 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 [1-4].

Except producing a good surface finish, the burnishing process has additional advantages over other machining processes, such as securing increased hardness, corrosion resistance, and fatigue life as a result of producing compressive residual stress. Residual stresses are probably the most important aspect in assessing integrity, because of their direct influence on performance in service. Thus, control of the burnishing process (burnishing conditions) in such a way as to produce compressive residual stresses in the surface region could lead to considerable improvement in component life [1-4]. A comprehensive classification of burnishing tools and their application has been given by Shneider [5]. A literature survey shows that work on the burnishing process has been conducted by many researchers and the process also improves the properties of the parts, e. g. higher wear resistance [6-8], increased hardness [10-12], surface quality [6, 9-11], and increased maximum residual stress in compression [10].

The parameters affecting the surface finish are: burnishing force, feed rate, ball material, number of passes, workpiece material, and lubrication [3, 6, 9]. It is necessary to find an optimal process condition capable of producing desired surface quality and hardness. However, this optimization should be performed in such a way that all objectives will be fulfilled simultaneously. Such an optimization technique is called multi-response optimization [12].

A literature survey shows that work on the burnishing process has been conducted by many researchers and the process also improves the properties of the parts, e. g. wear resistance [1, 9], hardness [2, 4, 5], surface quality [6-8] and increased maximum residual stress in compression [6, 9-12]. The parameters affecting the surface finish are: burnishing force, feed rate, ball material, number of passes, workpiece material, and lubrication [6, 9]. The majority of the research existing in literature on the effect of burnishing parameters on the burnished surface has been experimental in nature. Very few analytical models are available in the literature [3, 13].

In this study, neural network modelling was developed to predict surface roughness under different burnishing conditions of burnishing force (F), number of passes (N), feed rate (f), and burnishing speed (V). A regression model was also developed in order to determine the effects of burnishing parameters. Experimental data was obtained from performed experiments in burnishing process. The values predicted using regression and neural network models were compared with the experimental data and average absolute error was computed.

Experimental Details and Test Results

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 appropriate for the use in aerospace industry

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[13]. The chemical composition and mechanical properties of the workpiece material is given in Table 1.

The workpiece material, as shown in Figure 1, was prepared with the diameter of 30 mm and a length of 60 mm as a three part each having a length of 20 mm.

Machines and Equipments

A ball with a diameter of 18 mm was used for burnishing. The detailed drawing is shown in Figure 2. When the ball or roller is pressed against the surface of the metallic specimen, a pre-calibrated spring was compressed. This spring is being used mainly to reduce the possible sticking of the tool on the surface [3, 13].

As shown in Figure 3, the experiments were performed on a FANUC GT-250B CNC lathe. The burnishing tool was mounted on the CNC turret. Dry turning and burnishing were used in all experimental work, but first of all alcohol was used to clean the specimens before burnishing [3, 13]. Cleaning of the ball was carried out continuously in order to prevent entering any hard particles from the contact surface between the tool and the specimen, because such hard particles usually leave deep scratches, which may damage the burnished surface of the specimen.

Phynix TR-100 model surface roughness tester was used to measure the surface roughness of the burnished samples. Cut off length of 0.3 was chosen for each roughness measurement. Vickers microhardness tester with 100 g load (HV_{100}) was used in the microhardness measurements. Six measurements of surface roughness were performed from the samples and average of the values were used as surface roughness. The range of burnishing parameters used in this study is shown in Table 2.

After collecting the experimental data, regression and neural network techniques were carried out to predict and compare the values of surface roughness. Regression model was also developed in order to determine the effects of burnishing parameters. Regression equation was obtained by using Design-Expert v6.0 software and neural network modelling was developed by using Qwiknet v2.23 software. A comparison between regression and neural network was made to determine the performance of the developed models.

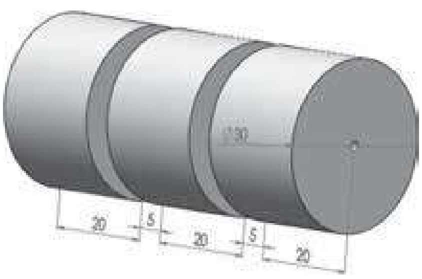


Figure 1. Dimensions of workpiece used in the experiments

Prediction Techniques

Regression Modelling. A scientific approach to plan experiments must be incorporated in order to perform an experiment most effectively. Statistical design of experiments is the process of planning experiments so that appropriate data could be collected which may be analyzed by statistical methods resulting in valid and objective conclusions [14, 15].

Factorial design is widely used in experiments involving several factors where it is necessary to investigate the joint effects of the factors on a response variable. A very important special case of factorial design is when each of the k factors of interest have only two levels. Full factorial design is often used to fit a first order response surface model and to generate the factor effect estimation. Factorial design has been employed to determine the minimum number of experiments to obtain an adequate model for the responses [15].

If surface roughness is represented by R_a, the linear regression equation for these experiments could be written as

$$R_a = a_0 + a_1x_1 + a_2x_2 + a_3x_3 + a_4x_4 + a_5x_1x_2 + a_6x_1x_3 + a_7x_1x_4 + a_8x_2x_3 + a_9x_2x_4 + a_{10}x_3x_4 \quad (1)$$

with a_0: response variable of surface roughness at base level, a_1, a_2, a_3, a_4: coefficients corresponding to each variable, a_1, a_5, a_6, a_7, a_8, a_9, a_{10}: interaction coefficients, x_1: burnishing force; x_2: number of passes, x_3: feed rate and x_4: burnishing speed at two levels are used to obtain a full two level factorial experiment or 2^k number of experiments.

chemical composition (%)	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 (HV_{100})
	220	95	150	160	150

Table 1. Chemical composition and mechanical properties of AA7075 aluminum alloy

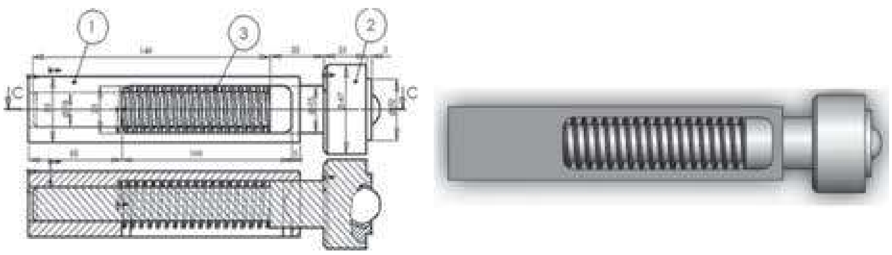
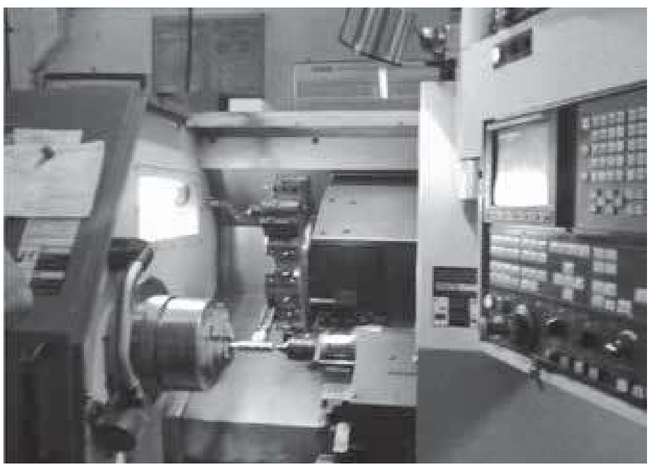


Figure 2. Drawing of ball burnishing tool, casing (1), adapter cover (2), spring (3) [13]

Figure 3. CNC experimental set up



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Neural Networks (NN). In recent years, neural networks have become a very useful tool in the modelling of input-output relationships of complicated systems. This is because neural networks have an excellent ability to learn and to generalize the complicated relationships between input and output variables [16]. There are several applications of neural networks such as back-propagation network (BPN). In general, BPN seems to be the most utilized neural network. A feed forward neural network based on back propagation is a multi-layered architecture made up of one or more hidden layers placed between the input and output layers [17]. Layers include several processing units known as neurons. They are connected with variable weights which need to be determined. The neurons of the input layer are used to receive the input vector of the system and the neurons of the output layer are used to generate the corresponding output vector of the system. The neuron evaluates the inputs and determines the strength of each one through its weighting factor, i. e. the larger the weight between two neurons, the stronger is the influence of the connection. The result of the summation function can be treated as an input for an activation function by which the output of the neuron is determined. The output of the neuron is then transmitted along the weighted outgoing connections to serve as an input to subsequent neurons. To modify the connection weights properly, a supervised learning algorithm involving two phases is employed [17, 18].

Modelling of surface roughness with neural networks is composed of two phases: training and testing of the neural networks with experimental data. As shown in Figure 4, in this study a 4-inputs, double 4 neuron hidden layers, and 1-output (4 : 4 : 4 : 1) type BPN algorithm was utilized to construct the BPN prediction model.

There are different learning strategies in neural network training such as supervised reinforcement learning and unsupervised learning. The learning set consists of the inputs and the outputs used in training the network. In the present study, the supervised learning approach was used as training method. The training set of the NN modelling is given in Table 3.

Results and Discussions

The regression equation obtained from regression analysis based on experiments of the training set can be expressed in Equation (2). After calculating each of the coefficients of Equation (1) and substituting the coded values of the variables for any experimental condition the linear regression equation for surface roughness can be obtained in actual factors as given in Equation (2).

$$R_a = 0.41317 + 0.029323F + 0.029176N - 0.56830f - 1.16289 \times 10^{-4}V + 7.42188 \times 10^{-3}FN + 0.023661Ff + 4.10156 \times 10^{-6}FV + 0.20357Nf + 4.53125 \times 10^{-5}NV + 6.25 \times 10^{-5}fV \quad (2)$$

This equation indicates that burnishing force and number of passes have the most significant effect on the surface roughness.

From Table 4, it is evident that for our set of data the neural network predicts a surface roughness that is nearer to the experimental values than the regression analysis. In the prediction of surface roughness values the average errors for regression and neural network are found to be as 1.16 % and 1.50 %, respectively.

According to the analysis of variance (ANOVA), as given in Table 5, the contribution order of the burnishing parameters has been found to be: burnishing force (73.66 %), number of passes

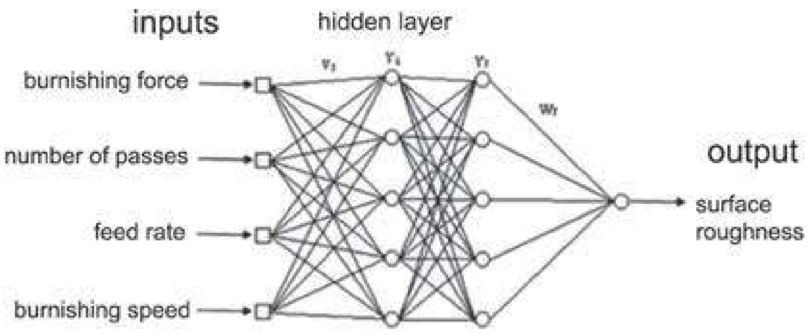

Figure 4. (4 : 4 : 4 : 1 type) BPN algorithm

Parameters	Low level (-1)	Base level (0)	High level (+1)
burnishing force, F, (kgf)	9	17	25
number of passes, N	2	3	4
feed rate, f, (mm/min)	0.27	0.53	0.80
burnishing speed, V, (rpm)	200	600	1000

Table 2. Range of burnishing parameters

Exp. no.	Burnishing force, F (kgf)	Number of passes N	Feed rate f (mm/min)	Burnishing speed V (rpm)	Surface roughness Ra (mm)
1	25	2	0.62	1000	1.92
2	9	2	0.62	1000	0.96
3	25	4	0.27	200	2.12
4	25	4	0.62	200	2.56
5	25	2	0.62	200	1.78
6	25	2	0.27	1000	1.67
7	25	2	0.27	200	1.75
8	9	2	0.27	1000	0.92
9	25	4	0.27	1000	2.44
10	9	2	0.62	200	0.89
11	9	2	0.27	200	0.82
12	9	4	0.27	1000	1.25
13	9	4	0.62	1000	1.45
14	9	4	0.62	200	1.35
15	9	4	0.27	200	1.25
16	25	4	0.62	1000	2.66

Table 3. Full factorial design matrix and neural network training set

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Exp. no.	Burnishing force (kgf)	Number of passes	Feed rate (mm/min)	Burnishing speed (rpm)	Surface roughness (µm)	Regression		NN	
						predicted	error %	predicted	error %
1	10	2	0.62	200	0.98	0.97	0.94	0.99	-1.02
2	9	3	0.45	800	1.13	1.15	-1.56	1.15	-1.77
3	25	2	0.8	400	1.97	1.97	-0.04	1.98	-0.51
4	16	2	0.45	400	1.25	1.30	-4.26	1.28	-2.40
5	18	3	0.45	1000	1.79	1.76	1.58	1.78	0.56
6	25	4	0.27	800	2.37	2.38	-0.37	2.38	-0.42
7	9	2	0.27	200	0.9	0.89	1.26	0.89	1.11
8	9	4	0.27	1000	1.32	1.30	1.24	1.31	0.76
9	10	4	0.45	800	1.42	1.44	-1.72	1.43	-0.70
10	9	3	0.62	600	1.15	1.18	-2.65	1.18	-2.61
11	16	3	0.27	200	1.4	1.46	-4.30	1.43	-2.14
12	9	2	0.45	800	0.92	0.92	-0.42	0.93	-1.09
13	25	4	0.62	1000	2.7	2.73	-1.13	2.68	0.74
14	16	4	0.62	200	1.88	1.90	-0.81	1.89	-0.53
15	18	4	0.27	200	1.8	1.80	-0.26	1.82	-1.11
			$\text{error\%} = \frac{(\text{experimental } R_a - \text{predicted } R_a)}{\text{experimental } R_a} \cdot 100$			average error = 1.16 %		average error = 1.50 %	

Table 4. Test and comparison set used for regression and neural network analysis

Parameter	Degree of freedom	Sum of square	Mean square	F	Contribution (%)
F	1	4.010	4.010	495.90	73.66
N	1	1.190	1.190	147.60	21.86
f	1	0.110	0.110	14.09	2.02
V	1	0.035	0.035	4.35	0.64
FxN	1	0.056	0.056	6.98	1.03
Fxf	1	0.018	0.018	2.17	0.33
FxV	1	0.0002	0.0002	0.34	0.01
Nxf	1	0.020	0.020	2.51	0.37
NxV	1	0.0005	0.0005	0.65	0.01
fxV	1	0.0003	0.0003	0.038	0.01
error	5	0.004	0.008		0.07
total	15	5.444			100

Table 5. ANOVA results of oblique turning process parameters

(21.86 %), feed rate (2.02 %), and burnishing speed (0.64 %).

It is clear from the response surface plots shown in Figures 5 to 7 that increasing burnishing force with an increase of the number of passes increased the surface roughness thus decreased the surface quality. Increasing feed rate with number of passes also increased the surface roughness. It is also found that burnishing speed has the lowest effect on surface roughness. Maximum surface quality (minimum roughness of 0.82 mm) is obtained with experiment 11 (F = 9 kgf, N = 2, f = 0.27 mm/min, V = 200 rpm). Minimum surface quality (maximum roughness of 2.66 mm) is obtained with experiment 16 (F = 25 kgf, N = 4, f = 0.62 mm/min, V = 1000 rpm).

The analysis results of the surface showed that the value of the multiple coefficient of R^2 is obtained as 0.99 (which means that the explanatory variables express 99 % of the variability in response variable) for neural network and 0.97 for regression analysis. The closer a value with adjusted R^2 to 1 the better fit it is. It is generally the best indicator of the fit quality and it was obtained as 0.99. The statistical analysis also proved that both methods fit well to the experimental observations. Figure 6 represents the comparison of predicted (both NN as well as regression) and actual results. Both regression as well as NN results showed that the predicted values and the respective fitted line are very close to the experimental values.

Conclusions

The prediction of optimal burnishing conditions for the required surface finish and dimensional accuracy plays a very important role in the process planning of the burnishing process. The following results can be drawn as conclusions from this study:

- Predictions of the response variables were made using factorial design as well as neural network techniques and the obtained values by both methods were compared with the experimental surface roughness values of the response variables to decide about the accuracy of predictions.
- The priority order of burnishing parameters was found to be: burnishing force, number of passes, feed rate, and burnishing velocity.
- Increasing burnishing force together with an increase of the number of passes caused an increase in surface roughness (decreased surface quality)

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- Feed rate and burnishing speed have small effect on surface roughness.
- The present case results showed that the accuracy of the neural network model is closer to the predictions of the experimental values of surface roughness compared to the regression analysis as the average errors of the surface roughness in the case of the neural network are lower than those obtained using regression analysis (average error is 1.16 % for NN compared to 1.50 % for regression predictions).

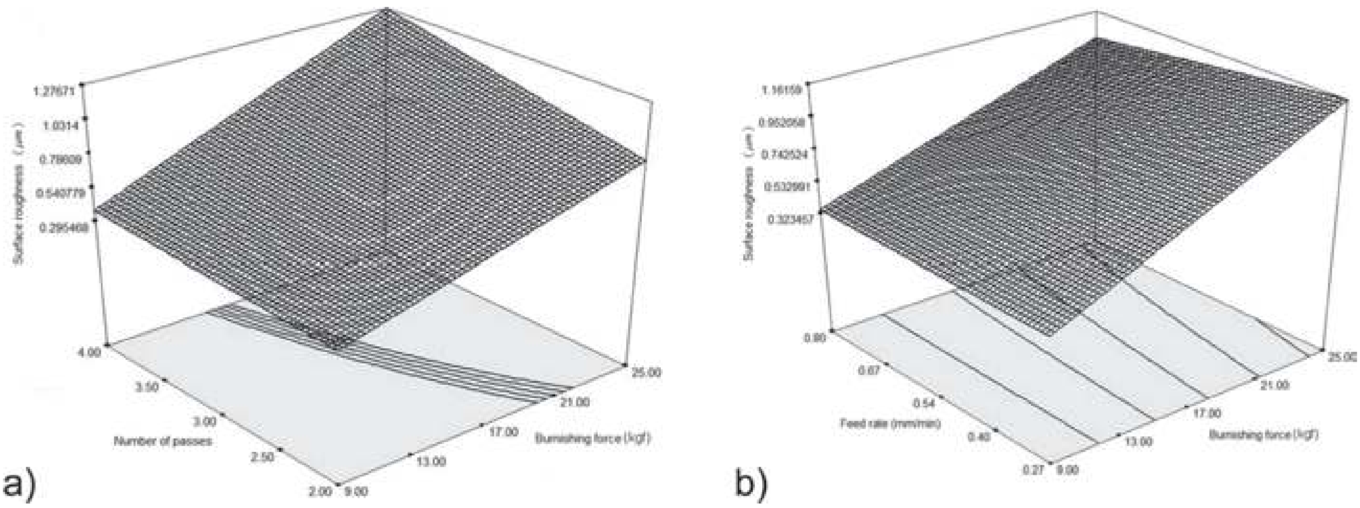

Figure 5. a) Effect of number of passes and burnishing speed on surface roughness, b) effect of feed rate and burnishing speed on surface roughness

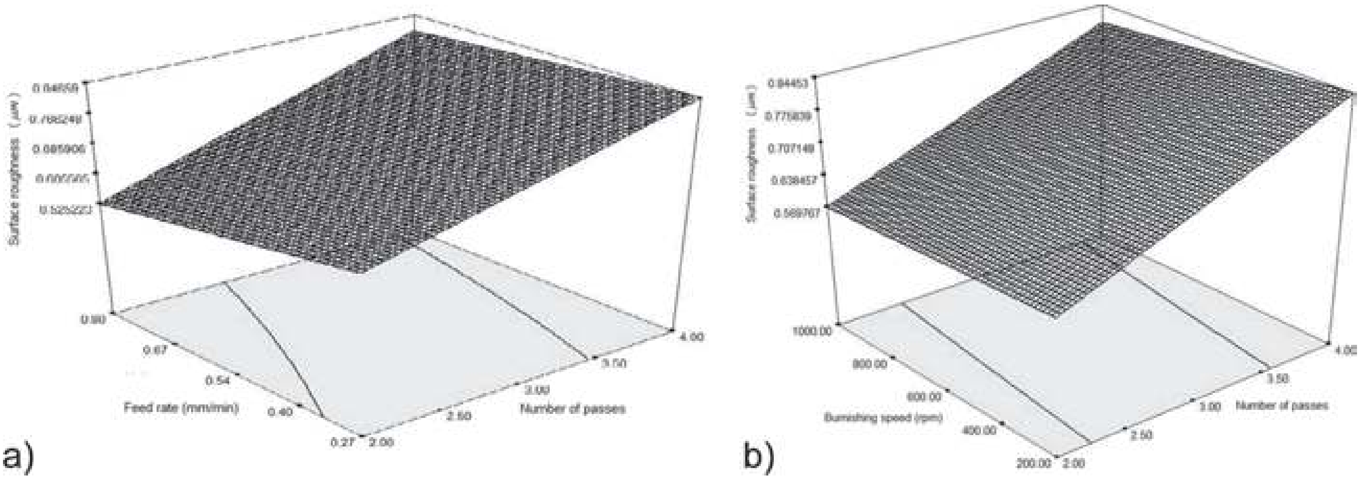

Figure 6. a) Effect of feed rate and number of passes on surface roughness, b) effect of burnishing speed and number of passes on surface roughness

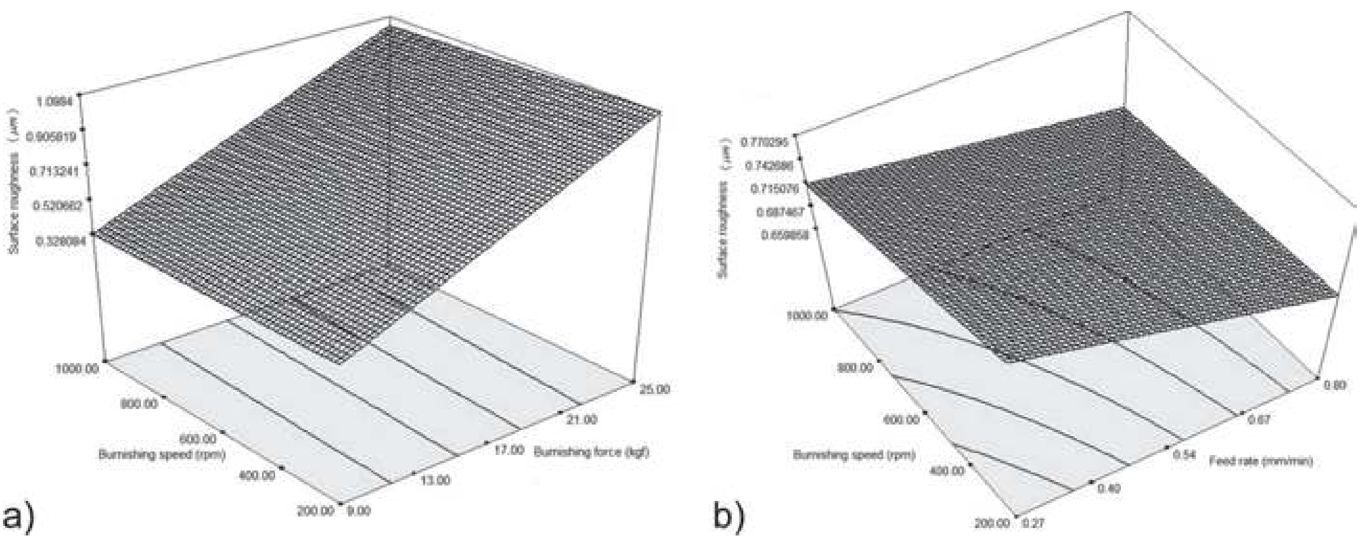

Figure 7. a) Effect of burnishing speed and burnishing force on surface roughness, b) effect of burnishing speed and feed rate on surface roughness

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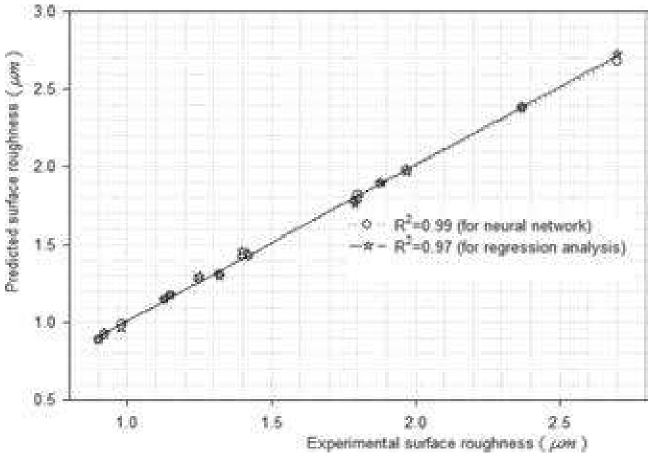

Figure 8. Comparison of experimental and predicted surface roughness

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Abstract

Vorhersagende Modellierung des Kugelpolierprozesses mittels Regressionsanalyse und Neuronalen Netzen. Der vorliegende Beitrag beleuchtet zwei der Techniken, nämlich die Regressionsanalyse und die Technik der Neuronalen Netze, um die Oberflächenrauheit bei einem Kugelstrahlprozess vorherzusagen. Die so ermittelte Oberflächenrauheiten wurden mit experimentell bestimmten Werten verglichen. Außerdem wurden die Auswirkungen der Hauptparameter des Polierens bezüglich Oberflächenrauheit bestimmt. Die Oberflächenrauheit (R_a) wurde als Antwortvariable und die Polierkraft, die Zahl der Polierdurchgänge, die Vorschubgeschwindigkeit und die Poliergeschwindigkeit wurden als Inputparameter herangezogen. Die Beziehung zwischen der Oberflächenrauheit und den Polierparametern wurde für die direkte Messung der Oberflächenrauheit herausgefunden. Die Ergebnisse zeigen die Anwendungsmöglichkeiten der Regressionsanalyse und des Modells der Neuronalen Netzen, um die Oberflächenrauheit exakt vorherzusagen.

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