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Artificial neural networks in mechanical surface enhancement technique for the prediction of surface roughness and microhardness of magnesium alloy

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Abstract. The artificial neural network method (ANN) is widely used in both modeling and optimization of manufacturing processes. Determination of optimum processing parameters plays a key role as far as both cost and time are concerned within the manufacturing sector. The burnishing process is simple, easy and cost-effective, and thus it is more common to replace other surface finishing processes in the manufacturing sector. This study investigates the effect of burnishing parameters such as the number of passes, burnishing force, burnishing speed and feed rate on the surface roughness and microhardness of an AZ91D magnesium alloy using different artificial neural network models (i.e. the function fitting neural network (FITNET), generalized regression neural network (GRNN), cascade-forward neural network (CFNN) and feed-forward neural network (FFNN). A total of 1440 different estimates were made by means of ANN methods using different parameters. The best average performance results for surface roughness and microhardness are obtained by the FITNET model (i.e. mean square error (MSE): 0.00060608, mean absolute error (MAE): 0.01556013, multiple correlation coefficient (R): 0.99944545), using the Bayesian regularization process (trainbr)). The FITNET model is followed by the FFNN (i.e. MAE: 0.01707086, MSE: 0.00072907, R: 0.99932069) and CFNN (i.e. MAE: 0.01759166, MSE: 0.00080154, R: 0.99924845) models with very small differences, respectively. The GRNN model has noted worse estimation results (i.e. MSE: 0.00198232, MAE: 0.02973829, R: 0.99900783) as compared with the other models. As a result, MSE, MAE and R values show that it is possible to predict the surface roughness and microhardness results of the burnishing process with high accuracy using ANN models.

Key words: artificial neural network, prediction, ball burnishing, magnesium alloys, AZ91D.

1. Introduction

Magnesium and its alloys are widely used in the manufacturing, aerospace, automotive and defense industries because of its low-density $(1.74\ \mathrm{g/cm^3})$, good toughness, rigidity and high machinability as well as its high strength/weight ratio. The use of magnesium alloys has recently increased further with the development of industry and technology [1–3]. Magnesium is increasingly taking its place within the industry with the development of technology [4, 5].

Surface roughness characteristics of machine parts used in the industry, especially in the manufacturing sector, are one of the factors that significantly affect machine performance and production cost [6]. Surface roughness plays a critical role in influencing the functional properties of machine parts due to friction, such as yield and tensile strength, fatigue strength, corrosion behavior and wear resistance [7–9]. The desired surface roughness value in the workpiece is difficult to achieve by means of traditional machining methods such as turning, milling and grinding.

The ball burnishing process is simple, practical and cost-effective, and it has started to frequently replace other surface treatment processes such as lapping, honing, grinding or polishing [8, 10]. It is preferred because of increasing surface roughness, fatigue strength and wear resistance of machine parts [8]. A schematic drawing of the ball burnishing process is shown in Fig. 1 [11]. During the burnishing process, a force is applied to the material surface by using hardened balls to

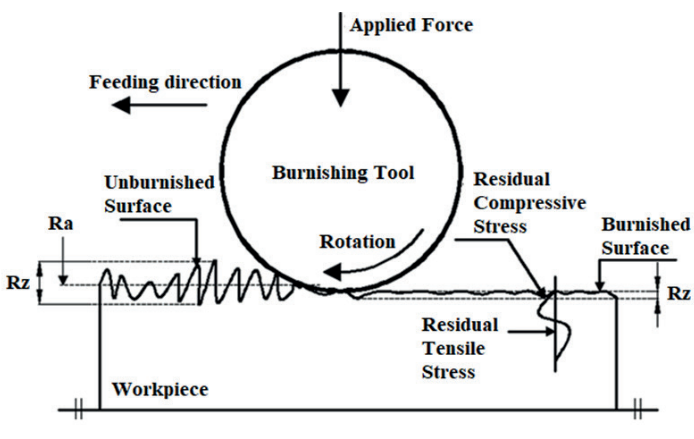

Fig. 1. Schematic drawing of the ball burnishing process [11]

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form a deformed layer on the surface. The amount of plastic deformation on the surface increases and the deformation hardens on the surface.

Factors comprising the ball burnishing process include the number of passes, burnishing force, burnishing speed, feed rate, ball material, workpiece material, ball size and lubricant. They all affect surface quality. Only a sole, very limited study has been devoted to modeling the ball burnishing process using the artificial neural network (ANN) method [12], although many researchers have been experimentally investigating the effects of force, speed, feed and passes [13–23]. There are many studies on methods such as turning and milling, which are traditional chip removal processes in the literature: Karkalos et al. [24] focused on the milling of the Ti-6Al-4V ELI titanium alloy by milling and then modeling this process. It has been attempted to estimate the surface quality of the workpiece and to find the cutting parameters required for minimum surface roughness. ANN models have been developed to allow for a more robust simulation model. Das et al. [25] used the ANN method to improve the ability to determine the effect of surface roughness of cutting parameters on the machining of metal matrix composites. An estimation model has been derived by Ali and Dhar [26] on surface roughness and tool wear using the ANN method. Abdullah et al. [27] applied turning at different parameters to determine the surface roughness of an AISI 4140 steel workpiece. They applied the ANN and Taguchi method to estimate the quality of the surface. Two different prediction methods were used in this study. The first one is ANN, relying on practical results, and the second is the method of regression analysis. The results show that neural networks are more effective than predictive regression analysis. Asilturk et al. [28] conducted a study on the estimation of surface quality after turning applied to an AISI 4140 steel workpiece. In these models, the cutting parameters are used as the input surface roughness output and 81 experiments are performed. The mean square error obtained using ANN is 0.002917120%. Jafarian et al. [29] researched various ANNs to minimize surface roughness and maximize tool life within the turning process. Three separate neural networks were used to predict outputs of the process by varying input machining parameters. A new method to train ANNs using evolutionary algorithms was proposed [29]. A comparison between the predicted results of the above-mentioned method and other ANNs trained by conventional methods has been made. Yalcin et al. [30] studied the cutting force, surface roughness and the temperature effect of the AISI 1050 steel subjected to face milling under different cutting parameters. In addition, the effect of the cutting parameters was investigated with the aid of trained ANNs using the results obtained from the Taguchi L_8 orthogonal design. Zuperl et al. [31] aimed at developing a reliable method for predicting 3D cutting forces during ball milling in their work. In this article, an ANN approach is used to develop a generalized model to estimate shear forces based on a series of intermittent cut conditions. The results obtained by applying a combination of the sigmoidal and Gaussian transfer function revealed that the accuracy of the neural network prediction is 98%. Quiza et al. [32] conducted a study to predict tool wear using neural networks in hardened D2 AISI steel in their study. Two models were constructed out to predict tool wear for different values of cutting speed, feed and time. One of them was based on the multilayer perceptron neural network, and the other was based on statistical regression. The design parameters and training process for the neural network were optimized using the Taguchi method. The results of the two models were analyzed and compared.

ANN methods are widely used to model and optimize the performance of manufacturing technologies. Determination of optimum processing parameters reduces cost and manufacturing time. The motivation of this study is to determine the optimum parameters for manufacturing low-cost and high-quality products and to shorten the production time of the manufacturing process using ANN methods.

The AZ91D magnesium alloy was burnished by using the mechanical surface enhancement technique of the ball burnishing operation designed by means of the L_{18} orthogonal Taguchi method. It is desirable to estimate the best values using the results obtained from this operation.

The purpose of this study is to predict surface roughness and microhardness of the AZ91D magnesium alloy using four ANN models. i.e. FFNN and FITNET, CFNN and GRNN. Burnishing parameters such as the number of passes, burnishing force, burnishing speed and feed rate have been used as input of the prediction ANN models.

2. Materials and methods

This section of the paper presents the Taguchi method and its use in the ball burnishing process of the AZ91D magnesium alloy, along with the experimental procedure, a review of ANN methods and features of the dataset which is used to develop ANN models.

2.1. Experimental design using the Taguchi method. The Taguchi method is widely used in engineering analysis. It constitutes an important tool for reducing the number of tests to be applied in experimental work in the manufacturing sector to a considerable extent and designing high-quality and cost-effective systems. [33]. Taguchi's parameter design provides a simple and systematic approach to optimizing the design for performance, quality and cost while remaining an important tool for robust design [33–37]. Selection of the orthogonal array is one of the important steps in the Taguchi method and it helps carry out experiments to determine optimum parameters.

The first step in the Taguchi method is the selection of an orthogonal array suitable for the parameters. The total degrees of freedom are calculated to select the appropriate orthogonal array for the design of the experiments. In this study, the burnishing force, burnishing speed and feed rate parameters are level 3 and passes are level 2. As a result, the degree of freedom is 11. According to the literature, the selected orthogonal array should have a degree of freedom greater than or equal to those of burnishing parameters in the Taguchi method [36]. Taking the variables into account, the Taguchi $L_{18}(2^2 \times 3^3)$ mixed orthogonal array was chosen as a suitable design for burnishing experiments (Table 1). The ball burnishing process parameters and their limits are presented in Table 2.

Table 1
Experimental layout using an L_{18} orthogonal array

Experiment number	Number of passes	Burnishing force	Burnishing speed	Feed rate
1	1	1	1	1
2	1	1	2	2
3	1	1	3	3
4	1	2	1	1
5	1	2	2	2
6	1	2	3	3
7	1	3	1	2
8	1	3	2	3
9	1	3	3	1
10	2	1	1	3
11	2	1	2	1
12	2	1	3	2
13	2	2	1	2
14	2	2	2	3
15	2	2	3	1
16	2	3	1	3
17	2	3	2	1
18	2	3	3	2

Table 2
Ball burnishing parameters and their limits

Factors	Level		
	1	2	3
Number of passes	1	2	–
Burnishing force (N)	50	150	250
Burnishing speed (rpm)	200	400	600
Feed rate (mm/min)	0.10	0.25	0.50

2.2. Experimental procedure. AZ91D magnesium alloy bars were used in ball burnishing experiments. In the experiments, two samples of the AZ91D magnesium alloy were used with a diameter of 35 mm and length of 200 mm. Each sample was divided into nine different sections, of a length of 25 mm and with a 5 mm slit between the pieces. Experiments were performed by applying different parameter values to each segment.

The ball burnishing process was performed on a CNC lathe machine (Fig. 2). The experimental set-up used for the burnishing experiments is shown in Fig. 3. A force gauge device was used to accurately determine force parameter values for the ball burnishing process. In these experiments, the ball used for burnishing was made of AISI 52100 steel with a hardness of 105 N/mm^2 and a diameter of 18 mm. The AZ91D magnesium alloy was burnished with a ball burnishing tool which has a Brinell hardness value of 78 N/mm^2. These hardness differences between the tool and the workpiece have a strong effect on

Fig. 2. Liouy Hsing GNC-450L CNC lathe

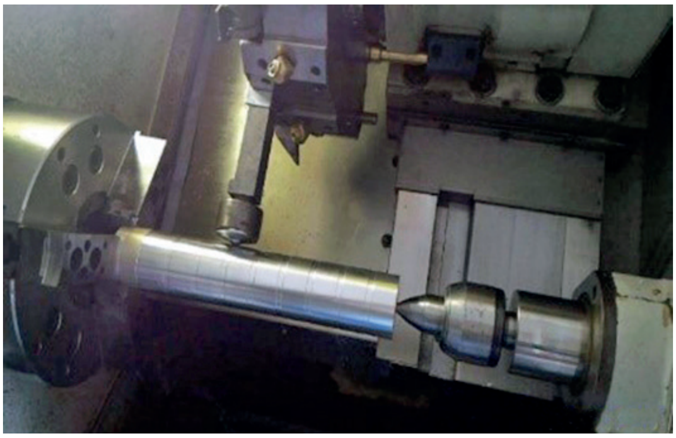

Fig. 3. Experimental set-up

the crushing resistance, depending on the compressive force applied.

Microhardness tests were carried out using a digital microhardness tester. The samples obtained were then subjected to a load of 9.81 N for 15 seconds as part of the Vickers microhardness test. Test results were evaluated by taking three valid measurements from all samples.

Surface roughness values were taken on three different segments of the workpiece material using portable roughness equipment.

2.3. Artificial neural networks (ANNs). A group of massively parallel architectures is known as ANNs, and they can learn and generalize from examples and experience [38]. Like neurons in the brain, a neural network includes processing elements. These processing elements form many simple computational elements that are lined up in layers. Through an ANN, the experimental results can be reproduced and approximated [39]. Four ANN models are proposed in this paper.

2.3.1. Feed-forward neural network (FFNN) and function fitting neural network (FITNET). FFNN is the simplest ANN model. Input, hidden and output layers form the FFNN

(Fig. 4). A backpropagation learning algorithm is used in these networks for learning. Weighted input signals are summed up and transferred by a nonlinear activation function. After that, the response of the network and actual observation results are compared. Then the network error, which is propagated backward through the system, is calculated. Afterwards, the algorithm updates the weight coefficients [40].

FITNET is a type of FNNN and it fits an input-output relationship. A FFNN that has one hidden layer and enough neurons in the hidden layers can be used for fitting any finite input-output mapping problem. FITNET uses TANSIG and PURELIN transfer functions in the hidden and output layers by default, respectively [41].

2.3.2. Cascade forward neural network (CFNN). CFNN has an input layer, one or more hidden layers and an output layer. Each subsequent layer of CFNN has weights and biases. All previous layers send weights to the following layers. The last layer of the network is the output layer [42]. The difference between CFNN and FFNN lies in the weight connection that starts from the input layer and continues along the following layers. Additional connections might improve the desired ANN learning speed [41].

2.3.3. Generalized regression neural network (GRNN). GRNN is based on kernel regression networks and it is a variation of radial basis neural networks. Backpropagation networks require an iterative training procedure. In contrast, GRNN does not require any training procedure and this fact makes it faster than the backpropagation networks. GRNN approximates any arbitrary function between input and output vectors and then function estimation is drawn directly from the training data [43].

2.4. Dataset design. The experimental results are used on datasets for different ANN models. A dataset comprises 72 samples and 6 attributes. The number of passes, burnishing force, burnishing speed and feed rate attributes are used as input data. Surface roughness and microhardness attributes are used as output data. The dataset's descriptive statistics are shown in Table 3.

The generated prediction models are evaluated by using six-fold cross-validation. The average error of estimates is predicted

Table 3
Dataset's descriptive statistics

Attributes		Minimum	Maximum	Mean	Standard deviation
Inputs	Number of passes	1	2	1.5	0.50
	Burnishing force	50	250	150	82.22
	Burnishing speed	200	600	400	164.44
	Feed rate	0.10	0.50	0.28	0.17

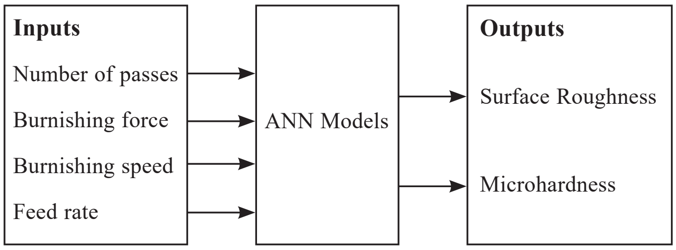

Fig. 4. ANN functional representation of input/output data

by means of cross-validation using the dataset with one individual attribute removed. 5/6 (i.e. 60 samples) of the training and 1/6 (i.e. 12 samples) of the test data form the cross-validated datasets. These parameters are used in the ANN networks as 4 input and 2 output parameters, as shown in Fig. 4.

Three performance measures (R, MSE and MAE) are calculated for all prediction models. Correlations between target and predicted values are measured with R. The average of the squares of the errors is measured with MSE. The closeness of the predictions to the target values is measured with MAE. The values of ANN design parameters are selected empirically. The best values are chosen after a number of experiments. Summaries of mathematical equations of these performance measures are given in equations 1, 2 and 3, respectively [44].

$$R = \sqrt{\frac{\sum_{i=1}^{n} (O_i - P_i)^2}{\sum_{i=1}^{n} (O_i - O_m)^2}} \tag{1}$$

$$MSE = \frac{1}{n}\left[\sum_{i=1}^{n} (O_i - P_i)^2\right] \tag{2}$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n} |O_i - P_i| \tag{3}$$

where n is the number of data points used for testing, O_i is the observed value, O_m is the average of the observed values and P_i is the predicted value. MATLAB (R2015b 64 bit) [41] was utilized for designing the proposed models and obtaining performance measures.

3. Results and discussion

3.1. Experimental results. In this study, the process parameters and experimental results obtained after the ball burnishing process are presented in Table 4. Ra is the value that defines the average of the grooves and peaks of a surface. The value of Rz is the average of the five highest and lowest heights. HV is the value obtained as a result of the Vickers microhardness test. Fig. 5. shows the variation of the S/N ratios calculated by taking

Table 4
Experimental results of the ball burnishing process

Experiments	Parameters				Experimental results			S/N ratio (dB)	
	Number of passes	Burnishing force	Burnishing speed	Feed rate	Ra (µm)	Rz (µm)	HV	Ra (µm)	HV
1	1	50	200	0.1	0.481	2.479	88.71	6.36	38.96
2	1	50	400	0.25	0.631	3.086	89.09	3.99	38.99
3	1	50	600	0.5	0.718	3.491	96.00	2.88	39.64
4	1	150	200	0.1	0.434	2.277	80.68	7.25	38.13
5	1	150	400	0.25	0.519	2.824	86.26	5.70	38.71
6	1	150	600	0.5	0.550	3.026	88.61	5.19	38.94
7	1	250	200	0.25	0.448	2.373	95.06	6.97	39.56
8	1	250	400	0.5	0.559	2.885	95.01	5.05	39.55
9	1	250	600	0.1	0.424	2.160	95.86	7.45	39.63
10	2	50	200	0.5	0.599	3.113	87.25	4.44	38.81
11	2	50	400	0.1	0.402	2.314	86.60	7.90	38.75
12	2	50	600	0.25	0.480	2.488	87.21	6.38	38.81
13	2	150	200	0.25	0.407	2.224	91.25	7.80	39.20
14	2	150	400	0.5	0.508	2.682	90.95	5.88	39.17
15	2	150	600	0.1	0.358	2.007	90.60	8.93	39.14
16	2	250	200	0.5	0.504	2.801	89.27	5.95	39.01
17	2	250	400	0.1	0.336	2.117	94.98	9.47	39.55
18	2	250	600	0.25	0.409	2.394	102.70	7.76	40.23

the results obtained from the tests into account. The "smaller is better"approach is used for surface roughness calculations and the "larger is better"approach is used for microhardness calculations.

In Fig. 5, it is seen that when the number of passes and force are increased, the roughness value of the surface to which the burnishing is applied decreases. As the number of passes increases, surface roughness improves due to excess microhardness on the surface [13, 45]. As the force applied to the surface increases, the surface roughness value decreases. This is due to the reduction of micro-cavities in the surface of the sample by increasing the pressure applied onto the surface [13]. The variation of burnishing speed does not cause a significant change in surface roughness. Moreover, as the feed value increases, surface roughness also increases. Thus, the surface properties deteriorate. Plastic deformation at the lower feed is more intensive and causes more increase in surface hardness. It seems that there more deformations occur at low feed rates. This is because the work hardening effect on the burnished surface is greater at lower feed rates [46]. Optimized ball burnishing parameters designed to obtain a smoother surface according to the graph generated by calculating the S/N ratios are: the number of passes: 2, burnishing force of 250 N, burnishing speed of 200 rpm and feed rate of 0.1 mm/min.

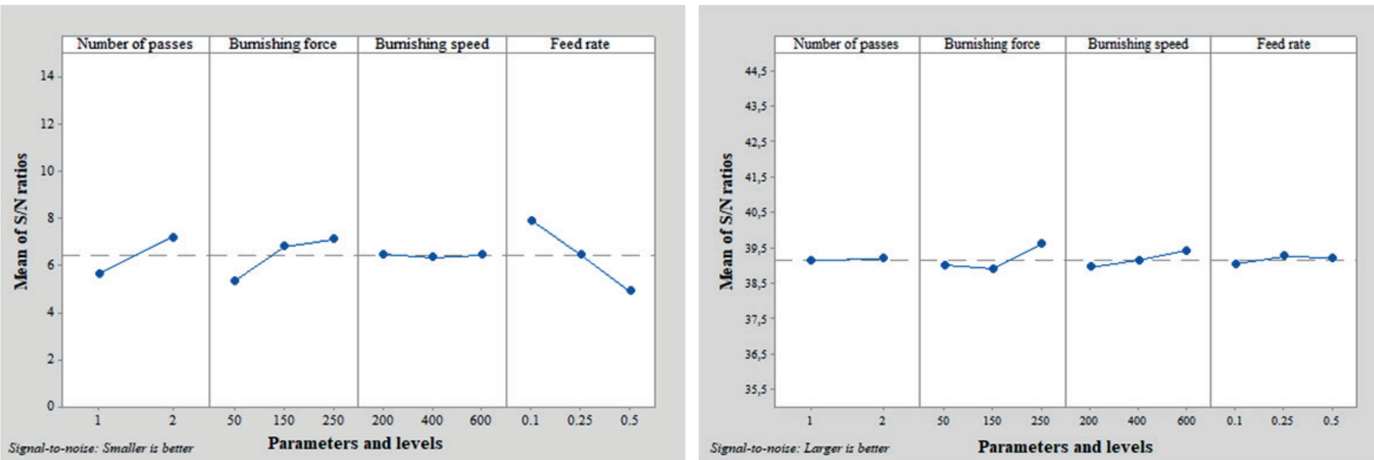

Fig. 5. Effects of parameters on surface roughness and microhardness

As the speed and the number of passes increase, the microhardness value of the material increases at a small rate. When the force increases from 50 N to 150 N, microhardness drops very slightly but it then increases a little between 150 N and 250 N. Due to increased metal flow, the cavities on the surface of the sample are decreasing. For this reason, the deformation of the material increases. The metal flow also increases and therefore the voids on the surface of the sample are reduced. In addition, the deformation of the material increases [45]. Microhardness is increased when the speed is increased to 200 rpm and 600 rpm. Also, when feed increases from 0.1 mm/min to 0.25 mm/min, microhardness increases but then it is reduced from 0.25 to 0.5. The reason is that at low feed, the effect of work hardening is higher on the surface to which burnishing is applied [46, 47]. In order to obtain a better microhardness value in the experiments, the burnishing parameters which are optimized based on the S/N ratios are as follows: the number of passes: 2, burnishing force: 250 N, burnishing speed: 600 rpm and feed rate: 0.25 mm/min. The graph of the effects of parameters on surface roughness and microhardness was obtained using the MINITAB 18 software program on the basis of experimental results. Furthermore, the S/N ratios are calculated using the MINITAB 18 software program.

Schematic representation of the ball burnishing force value is shown in Fig. 6. The force (Fz) is the actual force. The force applied to the ball is the measured force between the forces generated during the burnishing process. The measurement process was performed instantaneously. The burnishing force depends strongly on the burnishing speed and even feed [48]. According to the study by Kovacz et al. [48], the burnishing force is measured after the surface's smoothness of the workpiece is eliminated. It is strongly dependent on the burnishing speed and even feed.

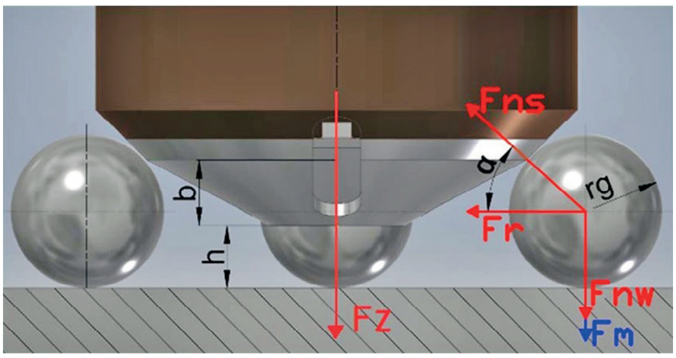

Fig. 6. Force generated during ball burnishing [48]

3.2. Prediction results of ANN models. In this study, a total of 1440 different estimates were made by means of the proposed methods for different parameters. 270, 540, 270 and 360 estimates were made by FFNN, FITNET, CFNN and GRNN, respectively.

According to Table 5, the FFNN, FITNET and CFNN methods have been tested with epoch numbers of 500, 1000 and 1500. The minimum gradients were used as 1×10^{-7}, 1×10^{-9} and 1×10^{-11}. TANSIG and LOGSIG transfer functions are used for the estimations. Hidden layers of the network structure are designed as 1, 2 and 3 layers. Each layer is tested with 5, 10, 15, 20 and 25 neurons.

Table 5
Parameters of FFNN, FITNET and CFNN methods

Network type	Estimates	Epoch number	Gradient	Trasfer function	Hidden layer of network structure	Neurons
FFNN	270	500	1×10^{-7}	TANSIG	1	5
						10
		1000	1×10^{-9}		2	15
				LOGSIG		20
		1500	1×10^{-11}		3	25
FITNET	540	500	1×10^{-7}	TANSIG	1	5
						10
		1000	1×10^{-9}		2	15
				LOGSIG		20
		1500	1×10^{-11}		3	25
CFNN	270	500	1×10^{-7}	TANSIG	1	5
						10
		1000	1×10^{-9}		2	15
				LOGSIG		20
		1500	1×10^{-11}		3	25

All these parameters are used together to make 270 different estimates. Weight and biases are randomly initialized. Also, train function, learning rate and momentum were used as trainbr, 0.02 and 0.5, respectively.

FITNET and CFNN methods have been tested with same parameters as the FFNN method. Only the FITNET method was tested with both trainbr and trainlm train functions. So, 540 different estimates were made for the FITNET method and 270 for CFNN.

Spread, which determines the generalization capability of GRNN, is the only parameter to change for the GRNN method. It was adopted between 1 and 90. For each spread value, the GRNN method has been run 4 times so that 360 different estimates were obtained. Table 6 lists the parameters used in the GRNN method.

Table 6
Parameters of GRNN method

Network type	Estimates	Spread	Number of trials
GRNN	360	1	90
		2	
		50	
		90	

Table 7 includes MSE, MAE and R results for surface roughness and microhardness attributes in the direction of the train function, the number of layers and spread parameters according

Table 7
Performance results of surface roughness and microhardness prediction using ANN prediction models
(Best results are outlined in bold)

Network type	Layer number	Train function	Surface roughness			Microhardness		
			MSE	MAE	R	MSE	MAE	R
FFNN	1	trainbr	0.00176266	0.03153937	0.99911813	**0.00008892**	0.00741008	**0.99995554**
FFNN	2	trainbr	0.00139800	0.02833287	0.99930066	0.00011303	0.00773669	0.99994348
FFNN	3	trainbr	0.00135803	0.02682043	0.99932069	0.00010012	0.00732129	0.99994994
FITNET	1	trainlm	0.00130431	0.02430685	0.99934757	0.00009662	0.00724314	0.99995169
FITNET	2	trainlm	0.00163820	0.03022628	0.99918050	0.00012326	0.00821088	0.99993837
FITNET	3	trainlm	0.00147856	0.02803173	0.99926042	0.00011331	**0.00702630**	0.99994334
FITNET	1	trainbr	0.00280989	0.03475843	0.99859368	0.00018883	0.01011976	0.99990558
FITNET	2	trainbr	**0.00110859**	**0.02392673**	**0.99944545**	0.00010357	0.00719353	0.99994822
FITNET	3	trainbr	0.00207860	0.03532469	0.99896008	0.00019316	0.01012355	0.99990342
CFNN	1	trainbr	0.00150250	0.02776128	0.99924845	0.00010059	0.00742205	0.99994971
CFNN	2	trainbr	0.00153044	0.02842476	0.99923443	0.00010561	0.00753309	0.99994719
CFNN	3	trainbr	0.00160366	0.02962260	0.99919783	0.00011638	0.00793599	0.99994181
GRNN	Spread = 1		0.00380355	0.04947831	0.99809621	0.00016109	0.00999828	0.99991945
GRNN	Spread = 2		0.00631043	0.06124830	0.99683921	0.00019560	0.01115283	0.99990220
GRNN	Spread = 50		0.00703572	0.06610467	0.99647579	0.00022721	0.01236774	0.99988639
GRNN	Spread = 90		0.00675712	0.06572829	0.99661457	0.00029595	0.01316236	0.99985201

to the four ANN models. When the results are examined, the following conclusions are reached:

- The best average performance results for surface roughness and microhardness were obtained using the "trainbr"training function in a two-layer FITNET model with 1000 epoch numbers using 20 neuron numbers in the LOGSIG transfer function with $1x10^{-11}$ gradients. "trainbr"is a network training function that updates the weight and bias values according to Levenberg-Marquardt optimization. It minimizes a combination of squared errors and weights, and then determines the correct combination so as to produce a network that generalizes well. The process is referred to as Bayesian regularization (Matlab, 2016) [41]
- The surface roughness value is best predicted by the two-layered FITNET model with "trainbr"training function.
- Optimum R and MSE values for microhardness are accomplished with the FFNN model, which uses a single-layer "trainbr"train function.
- The best MAE value for microhardness is obtained with the FITNET model, which uses a three-layer "trainlm"train function.
- The CFNN model showed average success in all results.
- The higher the number of layers in the CFNN model, the worse the results obtained.
- The GRNN model revealed worse results than other models for all R, MAE and MSE values.
- As the value of spread increased, the results of the GRNN model deteriorated. Best results are achieved when the spread value is 1.
- For the FITNET and FFNN models, clear difference in the number of layers could not be determined.

Table 8 presents average performance results of surface roughness and microhardness prediction using ANN prediction models. If a general assessment is made according to Table 5 and Table 8:

- The best results are obtained with the FITNET model.
- The FITNET model is followed by the FFNN and CFNN models with very small differences, respectively.
- The GRNN model achieved worse estimation results than other models, albeit very quickly, since it did not require a recurrent training procedure.
- When the average MSE, MAE and R values for surface roughness and microhardness are examined, the best results are obtained with the two-layered FITNET model with "trainbr"training function.

When the best results are obtained, the following values have been reached.

- The minimum MSE value is calculated as 0.00110859 for surface roughness and 0.00008892 for microhardness.
- 0.02392673 and 0.00702630 values are calculated as best MAE value for surface roughness and microhardness, respectively.
- The maximum R-value is calculated as 0.99944545 for surface roughness and 0.99995554 for microhardness.
- As evidenced by the values obtained, better results were obtained in predicting the microhardness attribute.

Table 8
Average performance results of surface roughness and microhardness prediction using ANN prediction models
(Best results are outlined in bold)

Network type	Layer number	Train function	Average results for surface roughness and microhardness		
			MSE	MAE	R
FFNN	1	trainbr	0.00092579	0.01947472	0.99911813
FFNN	2	trainbr	0.00072907	0.01707086	0.99930066
FFNN	3	trainbr	0.00075551	0.01803478	0.99932069
FITNET	1	trainlm	0.00070047	0.01577500	0.99934757
FITNET	2	trainlm	0.00088073	0.01921858	0.99918050
FITNET	3	trainlm	0.00079594	0.01752901	0.99926042
FITNET	1	trainbr	0.00149936	0.02243909	0.99859368
FITNET	2	trainbr	**0.00060608**	**0.01556013**	**0.99944545**
FITNET	3	trainbr	0.00113588	0.02272412	0.99896008
CFNN	1	trainbr	0.00080154	0.01759166	0.99924845
CFNN	2	trainbr	0.00081803	0.01797892	0.99923443
CFNN	3	trainbr	0.00086002	0.01877929	0.99919783
GRNN	Spread = 1		0.00198232	0.02973829	0.99900783
GRNN	Spread = 2		0.00325301	0.03620057	0.99837071
GRNN	Spread = 50		0.00363147	0.03923620	0.99818109
GRNN	Spread = 90		0.00352653	0.03944533	0.99823329

Figure 7 and 8 demonstrate the observed and predicted surface roughness values and microhardness values, respectively. The results obtained as a result of the experiments and the predicted data are very close to each other. In Table 9, the surface roughness and microhardness values obtained from the experiments are compared with the values obtained using the ANN models. As a result of the comparison, it is seen that the results are almost identical with the ANN models' results.

Table 9
Comparison of the results obtained with the ANN models and the experimental results

Sample number	Number of passes	Burnishing force	Burnishing speed	Feed rate	Observed surface roughness	Observed hardness	Predicted surface roughness	Predicted hardness	Success rate of surface roughness prediction	Success rate of microhardness prediction
1	1	50	200	0.10	0.451	87.89	0.475	87.93	0.946	0.999
2	2	250	400	0.10	0.336	94.98	0.327	96.25	0.973	0.986
3	1	50	600	0.50	0.686	98.25	0.711	96.10	0.963	0.978
4	2	50	400	0.10	0.393	85.08	0.391	84.70	0.994	0.995
5	2	250	400	0.10	0.374	92.44	0.349	95.47	0.933	0.967
6	1	50	600	0.50	0.718	96.00	0.712	95.14	0.991	0.991
7	1	150	200	0.10	0.434	80.68	0.421	80.97	0.970	0.996
8	1	250	200	0.25	0.447	98.98	0.453	97.26	0.986	0.982
9	1	250	600	0.10	0.488	95.97	0.471	96.68	0.965	0.992
10	1	50	200	0.10	0.503	90.20	0.542	91.02	0.922	0.990
11	2	150	600	0.10	0.358	90.60	0.371	92.36	0.963	0.980
12	2	150	400	0.50	0.490	92.44	0.476	92.89	0.971	0.995
							Average success rate		**0.964**	**0.987**

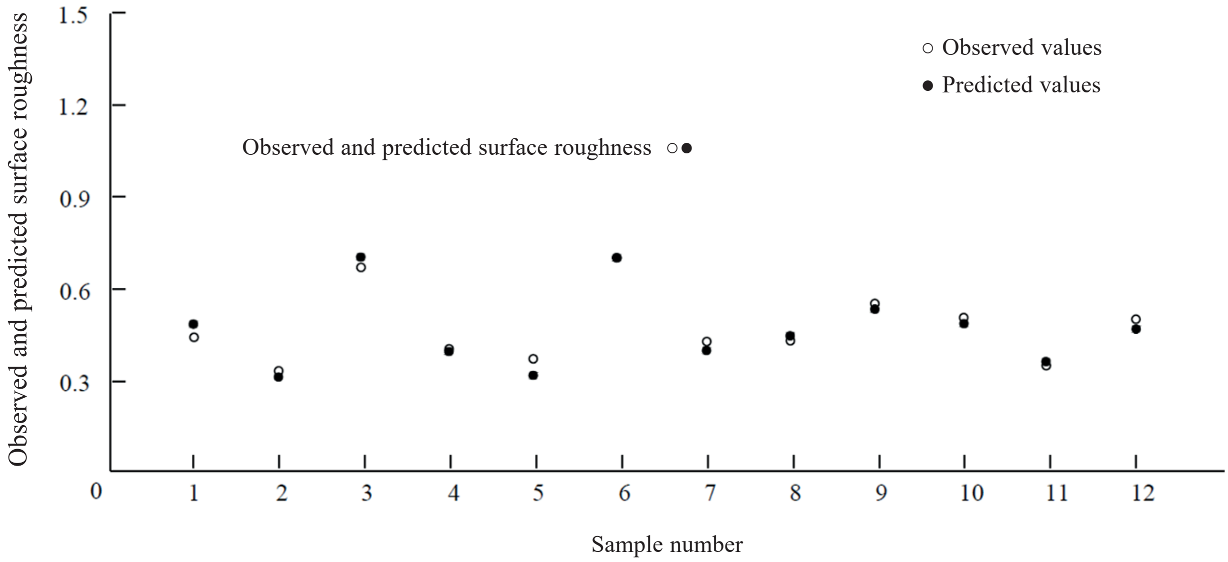

Fig. 7. Relation of the predicted values to the obtained surface roughness values

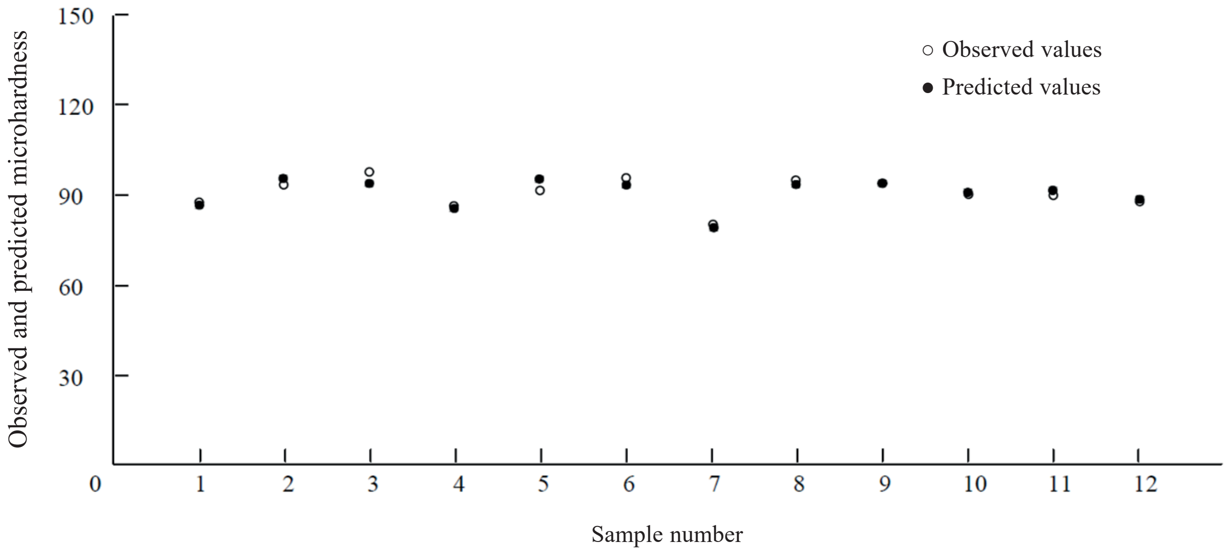

Fig. 8. Relation of the predicted values to the obtained microhardness values

4. Conclusions

In this paper, the effect of the burnishing parameters (number of passes, burnishing force, burnishing speed and feed rate) on surface roughness and microhardness were investigated using four artificial neural network models (FFNN, FITNET, CFNN, GRNN). The experimental design was carried out using the Taguchi method and the results obtained were compared with the prediction results of ANN models. The data obtained from the experiments are used as input values for the ANN method. Surface roughness and microhardness values of the material (AZ91D) have been estimated with very minor errors without performing the ball burnishing process. It is thus possible to manufacture high quality products at low cost, and to shorten the production period of the manufacturing process with the use of the ANN method in the manufacturing sector. The best average performance results for surface roughness and microhardness were obtained using the "trainbr"training function in a two-layer FITNET model with 1×10^{-11} gradient in LOGSIG transfer function, 20 neurons and 1000 epochs. The performance of the models can be summarized as follows: the FITNET model achieved average performance results of 0.00060608, 0.01556013 and 0.99944545 for MSE, MAE and R, respectively. It is followed by the FFNN model with 0.00072907 for MSE, 0.01707086 for MAE and 0.99932069 for R values. Also, the CFNN model achieved average results close to the FFNN model with MSE, MAE and R at 0.00080154, 0.01759166 and 0.99924845, respectively. The GRNN approach, however, has obtained worse estimation results than the other models. When the average MSE, MAE and R values for surface roughness and microhardness are examined, the best results are obtained with the two-layer FITNET model with "trainbr"training function. In this study, the success rates of the surface roughness and microhardness prediction results were yielded as 0.964 and 0.987, respectively, when using the ANN models. These results stand as sound proof that the usage of ANN models provides for time- and cost-saving in experimental studies.

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