IOP Conference Series: Materials Science and Engineering

PAPER • **OPEN ACCESS**

Prediction of roughness of planar surfaces processed with toroidal milling through an artificial neural network

To cite this article: A R Osan *et al* 2021 *IOP Conf. Ser.: Mater. Sci. Eng.* **1037** 012028

Prediction of roughness of planar surfaces processed with toroidal milling through an artificial neural network

A R Osan[1,2], M Banica[1] and V Nasui[1]

[1] Technical University of Cluj-Napoca North University Center of Baia Mare, Dr. Victor Babeş Street No. 62A, Romania

*Corresponding author's e-mail: osan.andrei@yahoo.com

Abstract. This paper is intended to create an artificial neural network capable of generating new values for the roughness on the basis of experimentally obtained data bases. Experimentally you will measure the roughness of the flat surfaces processed with the toroidal milling, the process factors being the input neurons of the neural network, following the roughness values being the output neurons. It aims to modify the input neurons from the same neural network and generate new roughness values.

1. Introduction

In recent years, artificial neural networks (RNA) are offered in front of the largest model offerings that can be kept and are now successful in certain engineering fields for modeling complex relationships difficult to describe with physical models.

Artificial neural networks have been widely applied in modeling many cutting operations, such as turning, drilling and milling [1]. Several researchers have used artificial neural networks to predict the influence of cutting parameters on production rate, production cost [2] or to predict the influence of cutting parameters on surface roughness [3], [4], tool wear [5]], [6] or the cutting force [1], [7].

Examples of optimization attempts can be found in the work of Mohana et al. [8] aimed at modeling surface roughness using neural networks. Genetic algorithms have been used in their research to optimize the weighting factors of the network. Ortiz-Rodrigues et al. [9] proposed the use of Taguchi methods (DOE technique) for robust RNA-driven design by the back propagation algorithm and develop a systematic and experimental strategy that emphasizes the simultaneous optimization of artificial neural network parameters under different conditions.

Several examples can be found in the works of Assarzadeh and Ghoreishi [11], meant to optimize the surface roughness using neural networks. The authors stated the effectiveness of using RNA to predict the removal rate of materials and Ra. In Hossain et al. [11], an RNA model was developed to investigate and predict the relationship between milling parameters and surface roughness during high-speed milling of Inconel 718 alloy. A very good predictive performance of the neural network was observed. Other approaches include the work of Panda and Mahapatra [12] in which the main components were used to model the drill wear. The main components of the drilling parameters were calculated and the networks were trained to predict them. The networks were able to classify low wear and high wear with an accuracy of 90% and to predict the wear of the main edge with an error of ± 6.5%.

MatLab® (MATrix LABoratory) is a high-performance, interactive software package for mathematical, scientific and engineering calculus. MatLab integrates calculation, programming and visualization, in a friendly work environment, solving problems involving the use of classical mathematical notations.

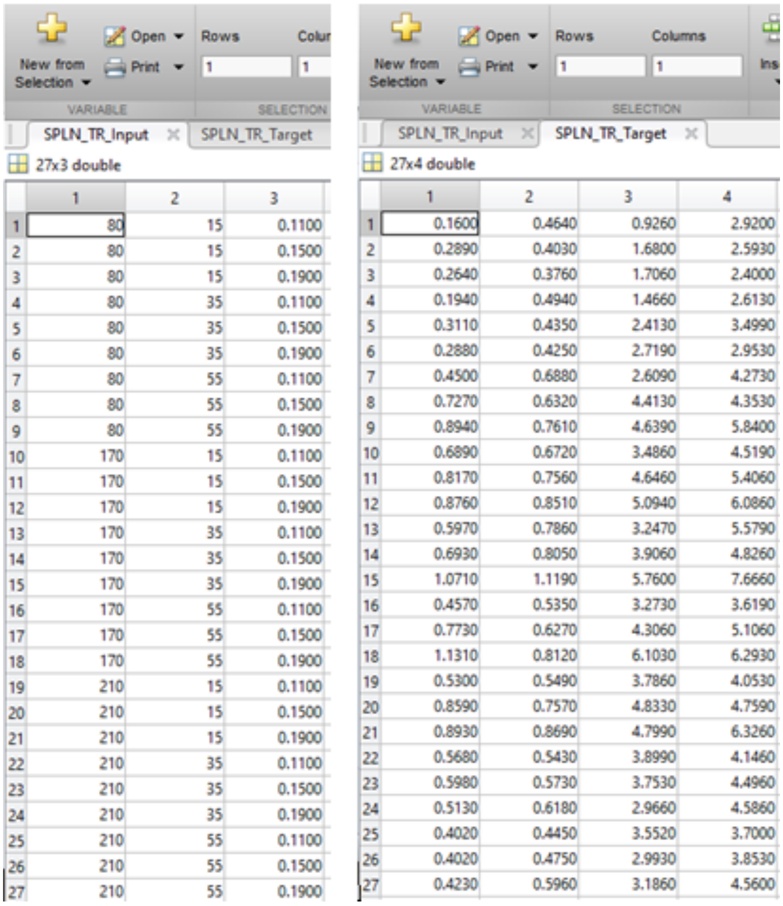
With tools and functions for managing large data sets, MatLab offers different types of specialized tools with machine learning, neural networks, deep learning, computer vision and machine learning.

Improving the generalization of the network helps prevent overload, a common problem in neural network design. Overload occurs when a network has memorized the training set, but has not learned to generalize to new entries. Overload produces a relatively small error on the training set, but a much larger error when new data is obtained in the neural network.

2. Approximation of functions with the artificial neural network

RNA approximation can be solved in MatLab:
From the command line, using specific functions Neural Network Toolbox;
Using the Neural Network Fitting Tool (nftool) graphical interfaces.

Before starting to create an artificial neural network, it is necessary to create input and output data. This is where computer resources based on previous research come in [13], [14], [15].



SPLN_TR_Input (27x3 double)

	1	2	3
1	80	15	0.1100
2	80	15	0.1500
3	80	15	0.1900
4	80	35	0.1100
5	80	35	0.1500
6	80	35	0.1900
7	80	55	0.1100
8	80	55	0.1500
9	80	55	0.1900
10	170	15	0.1100
11	170	15	0.1500
12	170	15	0.1900
13	170	35	0.1100
14	170	35	0.1500
15	170	35	0.1900
16	170	55	0.1100
17	170	55	0.1500
18	170	55	0.1900
19	210	15	0.1100
20	210	15	0.1500
21	210	15	0.1900
22	210	35	0.1100
23	210	35	0.1500
24	210	35	0.1900
25	210	55	0.1100
26	210	55	0.1500
27	210	55	0.1900

SPLN_TR_Target (27x4 double)

	1	2	3	4
1	0.1600	0.4640	0.9260	2.9200
2	0.2890	0.4030	1.6800	2.5930
3	0.2640	0.3760	1.7060	2.4000
4	0.1940	0.4940	1.4660	2.6130
5	0.3110	0.4350	2.4130	3.4990
6	0.2880	0.4250	2.7190	2.9530
7	0.4500	0.6880	2.6090	4.2730
8	0.7270	0.6320	4.4130	4.3530
9	0.8940	0.7610	4.6390	5.8400
10	0.6890	0.6720	3.4860	4.5190
11	0.8170	0.7560	4.6460	5.4060
12	0.8760	0.8510	5.0940	6.0860
13	0.5970	0.7860	3.2470	5.5790
14	0.6930	0.8050	3.9060	4.8260
15	1.0710	1.1190	5.7600	7.6660
16	0.4570	0.5350	3.2730	3.6190
17	0.7730	0.6270	4.3060	5.1060
18	1.1310	0.8120	6.1030	6.2930
19	0.5300	0.5490	3.7860	4.0530
20	0.8590	0.7570	4.8330	4.7590
21	0.8930	0.8690	4.7990	6.3260
22	0.5680	0.5430	3.8990	4.1460
23	0.5980	0.5730	3.7530	4.4960
24	0.5130	0.6180	2.9660	4.5860
25	0.4020	0.4450	3.5520	3.7000
26	0.4020	0.4750	2.9930	3.8530
27	0.4230	0.5960	3.1860	4.5600

Figure 1. Images with input data and target data of the neural network.

To create the input data and the output data, we chose to debate the quality of the flat surfaces obtained with the toroidal milling cutter. Thus, the input data are the three process variables. These are the cutting speed, the feed on the tooth and the angle of inclination. As for the output data, the target information, they are represented by the average values of Ra, measured parallel and perpendicular as well as by the average values of Rt, measured parallel and perpendicular. Therefore, the input data and the output data are shown in Figure 1.

To approximate the functions with artificial neural networks, using the graphical interfaces, the Neural Network Fitting Tool interface will be opened with the command "nftool".

This type of neural network is able to associate an input data set with a target data set for estimating certain values. This application has the function of helping to select data, to create and train a neural network, as well as to evaluate performance.

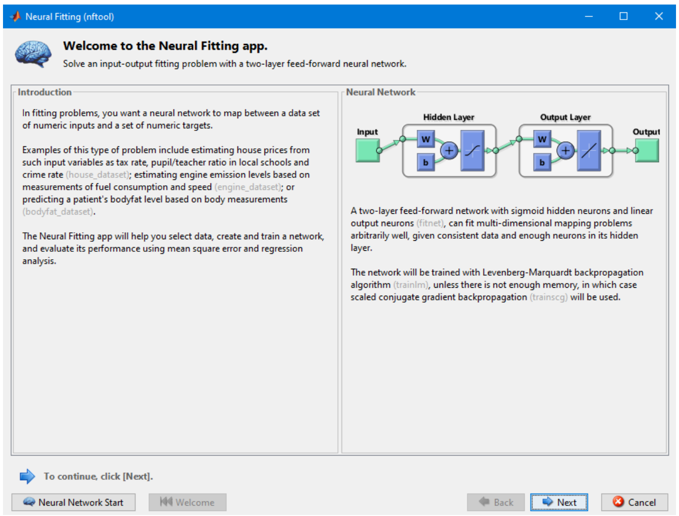


Figure 2. Neural Fitting Tool.

It has a power supply network with two layers of hidden neurons being trained with a back propagation algorithm as shown in Figure 2.

The next step in creating a neural network is to load the input and target data, as well as select the type of matrix, as shown in Figure 3.

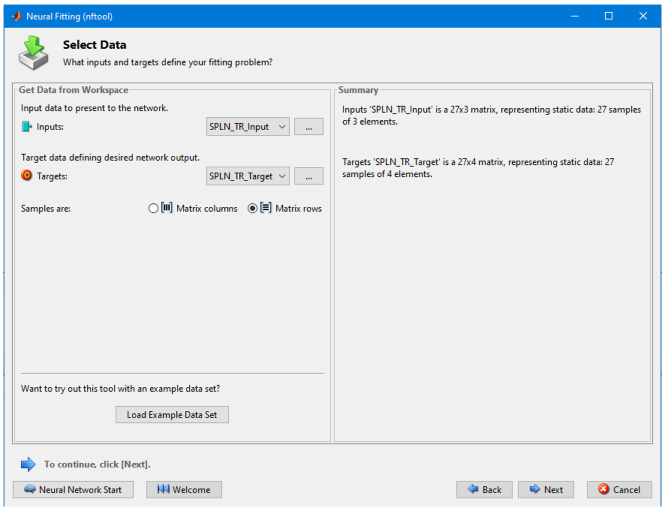


Figure 3. Selection of input and target data for RNA creation.

The next step is illustrated in Figure 4 and represents the establishment of the data assigned to the neural network training, but also the establishment of the number of values assigned to the network validation and testing function.

In this case, we chose to use 25 values for the training function, leaving only one for validation and testing.

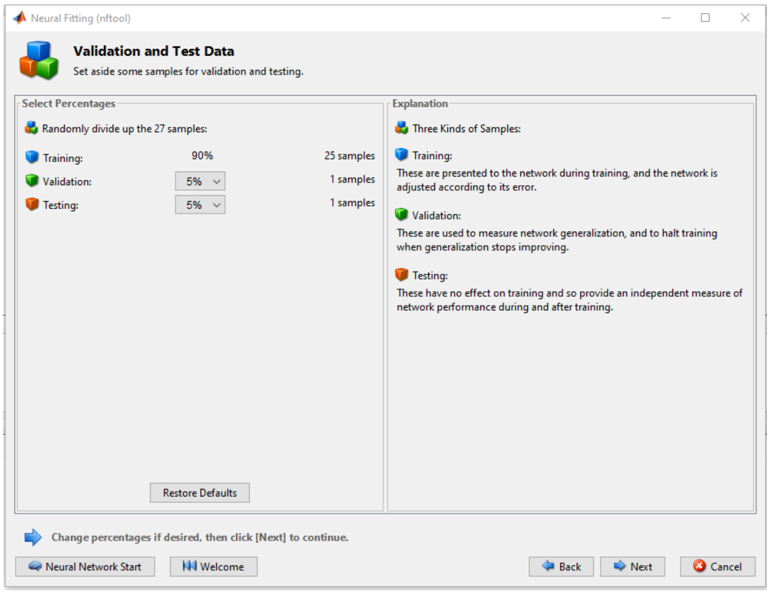


Figure 4. Selection of percentages assigned to neural network training, validation and testing.

Regarding the network architecture, here are defined the number of hidden neurons of the neural network, in our case we decided to use 20 neurons for the network to function in optimal conditions, as shown in Figure 5.

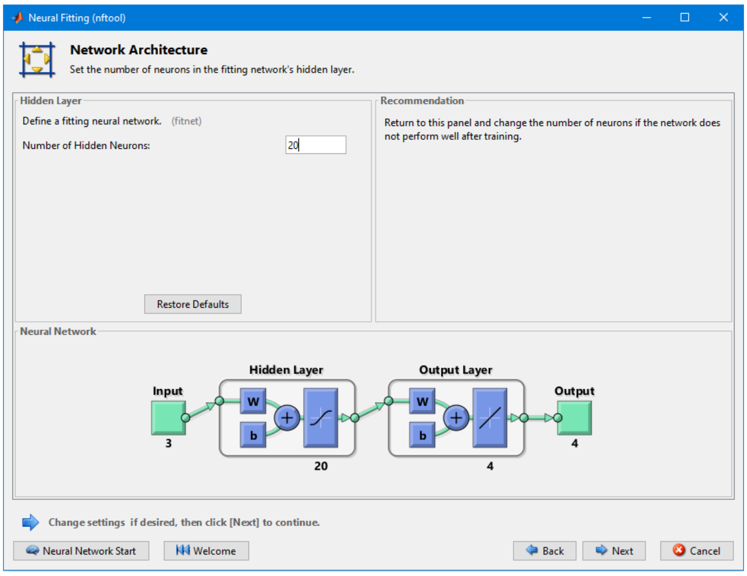


Figure 5. Neural network architecture.

Once the input data are established, the percentage of training, validation, testing, as well as the number of hidden neurons can only be transmitted to the network to learn the working algorithm, as in Figure 6. Following the training of the neural network, it transmits a series of indices, these are shown in Figure 7.

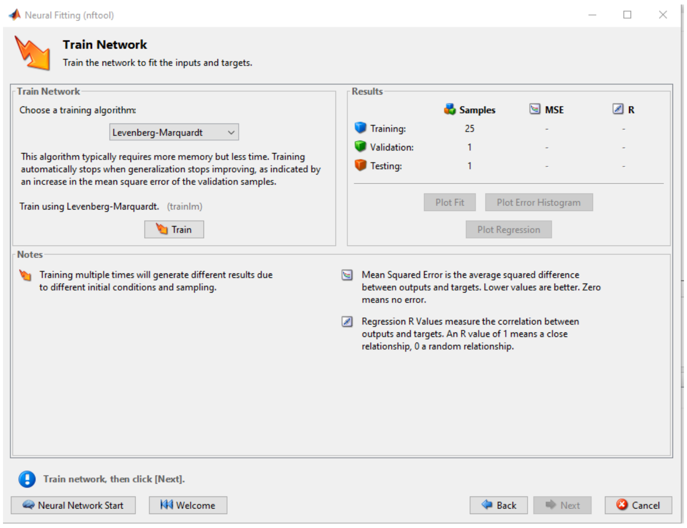


Figure 6. Neural network training model.

Figure 7. Neural network training.

Following the training of the network, it provides some information about the network, one of the information is supported by the number of interactions within the network, in this case it is about 9 interactions or 9 periods as shown in Figure 8.

In terms of network performance, the best performance was recorded during interaction number 3.

The training conditions of the neural network are dependent on the value of the gradient, which is a vector field whose vectors are directed in the direction of the highest growth rate of the scalar field. Thus, the mode is the highest rate of change, the maximum value being performed in the case of interaction number 9. The validation checks were 6, also at interaction 9, being presented in figure 9.

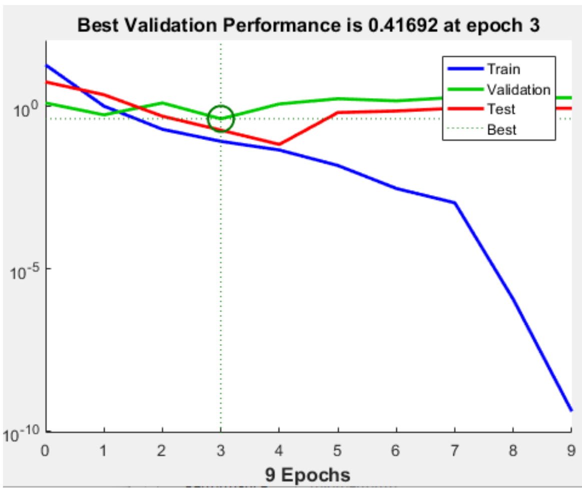


Figure 8. Neural network performance.

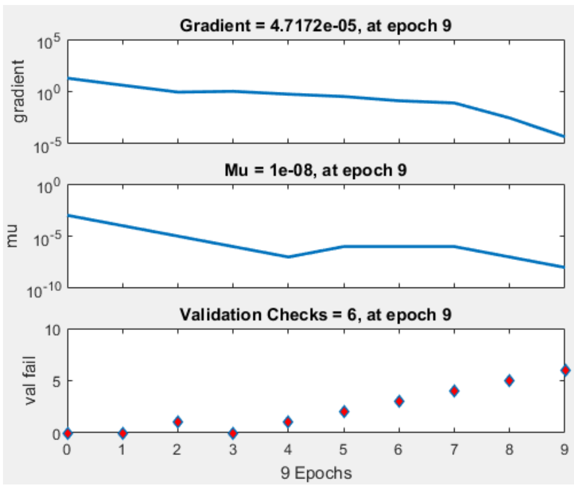


Figure 9. Training conditions.

Any system also has a series of errors, in the case of the neural network created, it has the most common type of error of 0.01469, as shown in Figure 10.

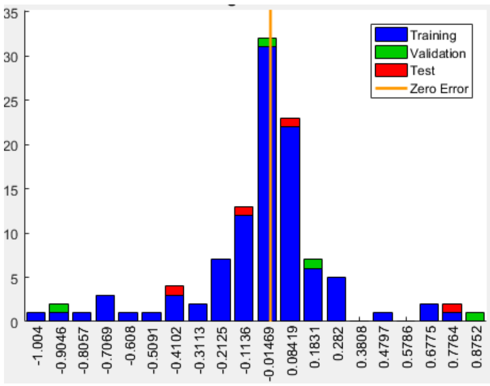


Figure10. Histogram of errors.

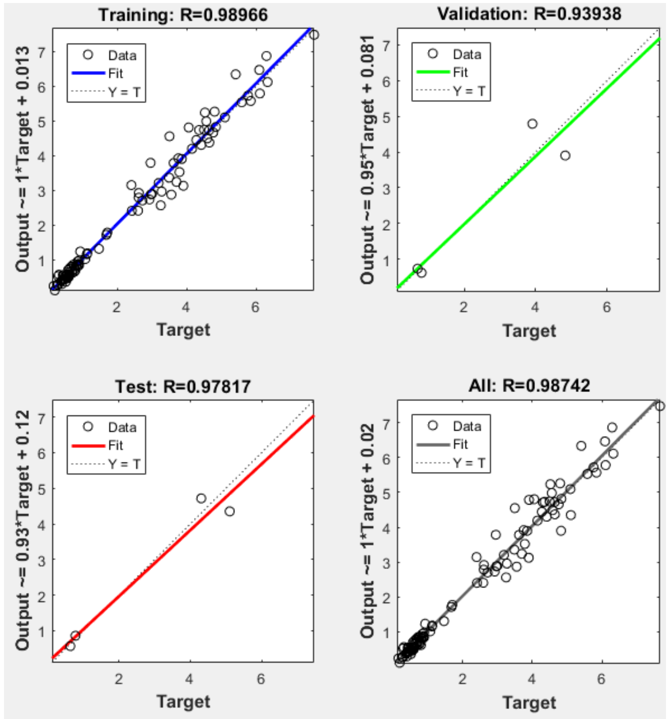


Figure 11. Linear regression of the neural network.

Regarding the linear regression, in the case of the artificial neural network studied and created on the surface quality, this is illustrated in figure 11, both in terms of training and validation and testing of the network.

For the implementation of the solutions in the next subchapter is presented the MatLab function as matrix support. The neural network diagram consists of 3 input neurons, 20 hidden neurons and 4 output neurons, as in Figure 12.

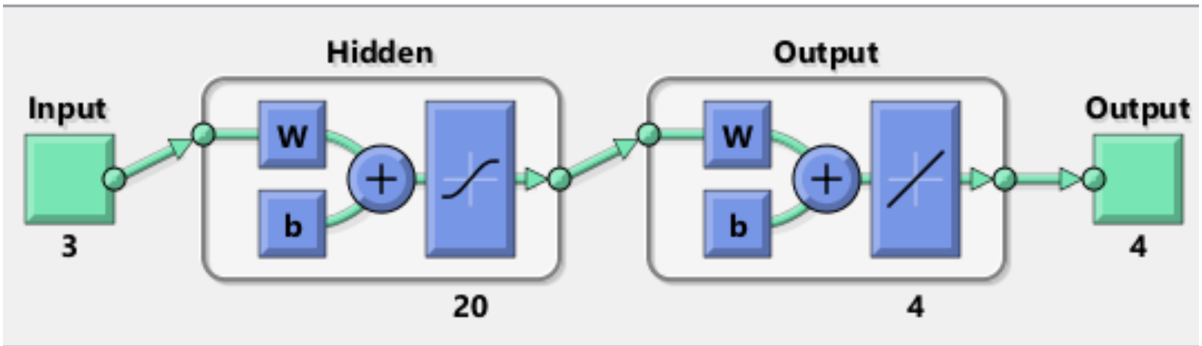


Figure 12. Diagram of the neural network.

Once the whole process of creating and training the neural network is completed, all that remains is to put the target data face to face with the outputs that the network offers.

In the next chapter are highlighted the measured data of roughness, having as input the three variables, and in comparison are the approximate values obtained after training the neural network, with a column with network errors attached.

3. Comparison of approximations

According to the previous chapter, where a neural network was created and trained using MatLab software, this network is able to approximate the output values based on the input values. As established, the network was created on the flat surface processed with toroidal milling cutter to approximate the roughness values. As input data, the input neurons are the three variables, the cutting speed, the feedrate on the tooth and the angle of inclination of the tool axis. The target values, output neurons are represented by the measured values both parallel and perpendicular to the roughness Ra and Rt, so there are 4 output neurons.

Table 1. Approximate values of RNA for the Ra quality of the flat surface processed with the toroidal milling cutter.

Surface type	Roughness R_a[µm]				Parallel Ra approximation error	Perpendicular approximation error Ra
	Real values		Approximate RNA values			
	The direction of measurement in relation to the direction of advance					
	Parallel	Perpendicular	Parallel	Perpendicular		
SPLN -TR-1	0.160	0.464	0.241	0.426	-0.081	0.038
SPLN -TR-2	0.289	0.403	0.270	0.397	0.019	0.006
SPLN -TR-3	0.264	0.376	0.279	0.372	-0.015	0.004
SPLN -TR-4	0.194	0.494	0.116	0.505	0.078	-0.011
SPLN -TR-5	0.311	0.435	0.566	0.517	-0.255	-0.082
SPLN -TR-6	0.288	0.425	0.525	0.552	-0.237	-0.127
SPLN -TR-7	0.450	0.688	0.462	0.684	-0.012	0.004
SPLN -TR-8	0.727	0.632	0.857	0.578	-0.130	0.054
SPLN -TR-9	0.894	0.761	0.975	0.651	-0.081	0.110
SPLN -TR-10	0.689	0.672	0.610	0.802	0.079	-0.130
SPLN -TR-11	0.817	0.756	0.822	0.811	-0.005	-0.055
SPLN -TR-12	0.876	0.851	0.884	0.947	-0.008	-0.096
SPLN -TR-13	0.597	0.786	0.499	0.691	0.098	0.095
SPLN -TR-14	0.693	0.805	0.737	0.622	-0.044	0.183
SPLN -TR-15	1.071	1.119	1.016	1.157	0.055	-0.038
SPLN -TR-16	0.457	0.535	0.555	0.463	-0.098	0.072
SPLN -TR-17	0.773	0.627	0.859	0.569	-0.086	0.058
SPLN-TR-18	1.131	0.812	1.182	0.848	-0.051	-0.036
SPLN -TR-19	0.530	0.549	0.540	0.579	-0.010	-0.030
SPLN -TR-20	0.859	0.757	0.813	0.731	0.046	0.026
SPLN -TR-21	0.893	0.869	0.840	0.874	0.053	-0.005
SPLN -TR-22	0.568	0.543	0.464	0.548	0.104	-0.005
SPLN -TR-23	0.598	0.573	0.517	0.698	0.081	-0.125
SPLN -TR-24	0.513	0.618	0.362	0.745	0.151	-0.127
SPLN -TR-25	0.402	0.445	0.423	0.416	-0.021	0.029
SPLN -TR-26	0.402	0.475	0.298	0.452	0.104	0.023
SPLN -TR-27	0.423	0.596	0.445	0.640	-0.022	-0.044

Table 1 shows the roughness values Ra measured parallel and perpendicular to the direction of advance, as well as the approximate values using the neural network, also on the two measuring directions.

From a percentage point of view, the nearest value is in the case of the flat surface with number 11, processed with the toroidal milling cutter (SPLN-TR-11) with an approximation error of 0.61% with a difference of 0.005 µm for the value measured in parallel , and for the value measured perpendicularly, the nearest value is in the case of the flat surface number 7, processed with the toroidal milling cutter (SPLN-TR-7) with an error of 0.58%, with a difference of 0.004 µm. The graphical representation is shown in Figure 13.

The largest error identified is in the case of the SPLN-TR-5 surface, measured in parallel with an approximation error of 81.9% and a difference of 0.255 µm, and in the case of perpendicular measurement, the largest error obtained is 22.7 %, for the surface of SPLN-TR-14 with a difference of 0.183 µm.

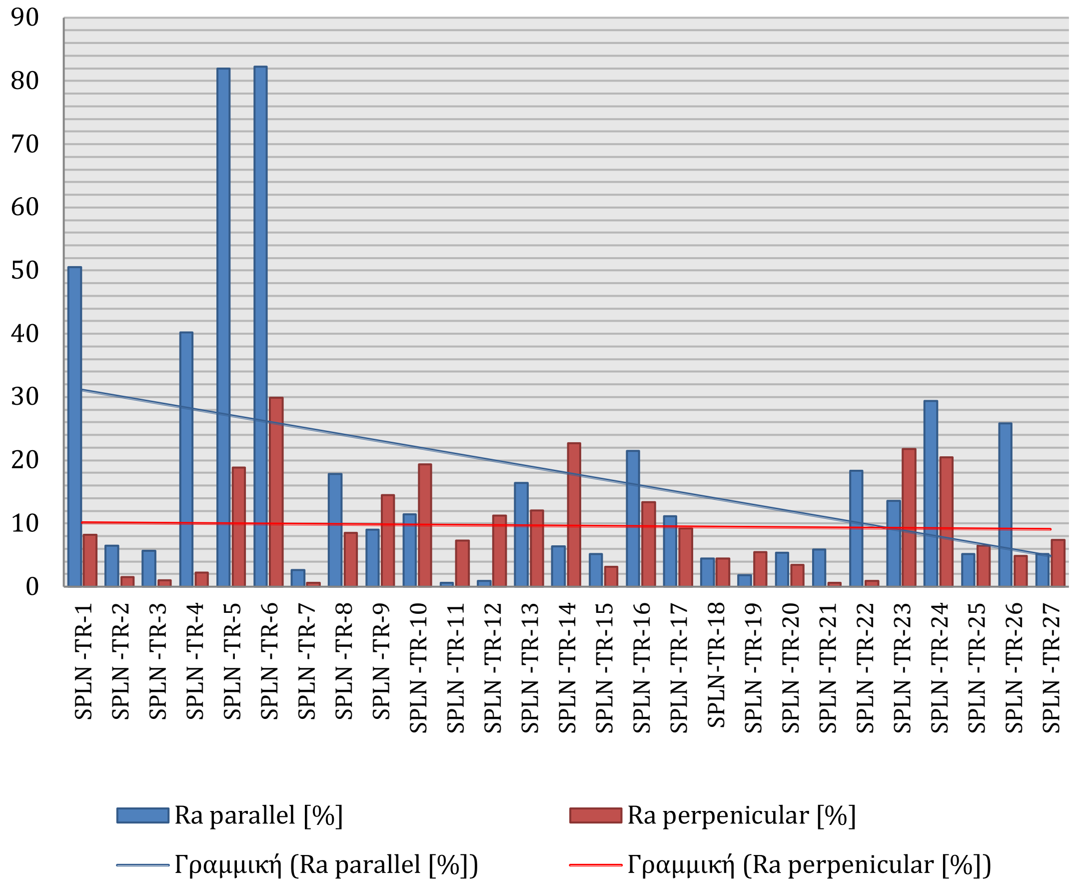


Figure 13. Graphical representation of the percentage error diagram for the approximate values Ra.

Table 2 represents the values of the roughness Rt measured on the flat surface processed with the toroidal milling cutter, and in comparison the approximate values are passed with the help of the neural network, following in the columns on the right to represent the approximation errors of the neural network.

In terms of percentage, the lowest value was made on the flat surface with number 12, processed with toroidal milling cutter (SPLN-TR-12) with a percentage of 0.27% and a minimum difference of 0.003 µm, determined value on the measuring direction parallel to the feed direction.

The lowest percentage value recorded in the direction of perpendicular measurement shall be 0.86% over the flat surface number 13 (SPLN-TR-13) with a difference of 0.048 µm.

Table 2. Approximate values of RNA for the Rt quality of the flat surface processed with the toroidal milling cutter.

Surface type	Roughness R_t[µm] – Real values – Parallel	Roughness R_t[µm] – Real values – Perpendicular	Roughness R_t[µm] – Approximate RNA values – Parallel	Roughness R_t[µm] – Approximate RNA values – Perpendicular	Parallel Rt approximation error	Perpendicular Rt approximation error
SPLN -TR-1	0.926	2.920	1.235	2.733	-0.309	0.187
SPLN -TR-2	1.680	2.593	1.715	2.410	-0.035	0.183
SPLN -TR-3	1.706	2.400	1.776	3.147	-0.070	-0.747
SPLN -TR-4	1.466	2.613	1.311	2.920	0.155	-0.307
SPLN -TR-5	2.413	3.499	2.406	4.552	0.007	-1.053
SPLN -TR-6	2.719	2.953	2.704	3.786	0.015	-0.833
SPLN -TR-7	2.609	4.273	2.786	4.445	-0.177	-0.172
SPLN -TR-8	4.413	4.353	4.303	4.733	0.110	-0.380
SPLN -TR-9	4.639	5.840	4.723	5.571	-0.084	0.269
SPLN -TR-10	3.486	4.519	3.361	5.236	0.125	-0.717
SPLN -TR-11	4.646	5.406	4.372	6.337	0.274	-0.931
SPLN -TR-12	5.094	6.086	5.097	6.465	-0.003	-0.379
SPLN -TR-13	3.247	5.579	2.563	5.531	0.684	0.048
SPLN -TR-14	3.906	4.826	4.788	3.901	-0.882	0.925
SPLN -TR-15	5.760	7.666	5.722	7.477	0.038	0.189
SPLN -TR-16	3.273	3.619	2.961	3.782	0.312	-0.163
SPLN -TR-17	4.306	5.106	4.716	4.352	-0.410	0.754
SPLN-TR-18	6.103	6.293	5.785	6.865	0.318	-0.572
SPLN -TR-19	3.786	4.053	3.523	4.806	0.263	-0.753
SPLN -TR-20	4.833	4.759	4.820	4.660	0.013	0.099
SPLN -TR-21	4.799	6.326	5.262	6.114	-0.463	0.212
SPLN -TR-22	3.899	4.146	3.127	4.193	0.772	-0.047
SPLN -TR-23	3.753	4.496	3.920	4.741	-0.167	-0.245
SPLN -TR-24	2.966	4.586	2.880	4.492	0.086	0.094
SPLN -TR-25	3.552	3.700	2.871	3.239	0.681	0.461
SPLN -TR-26	2.993	3.853	2.892	3.900	0.101	-0.047
SPLN -TR-27	3.186	4.560	3.206	4.985	-0.020	-0.425

The direction of measurement in relation to the direction of advance: Parallel / Perpendicular.

The maximum approximate percentage value was obtained on the palmar surface number 1 (SPLN-TR-1) with an error rate of 33.37% and a difference of 0.309 µm on the parallel measuring direction and on the perpendicular measuring direction, the maximum percentage value given is 30.09% with a difference of 1.053 μm.

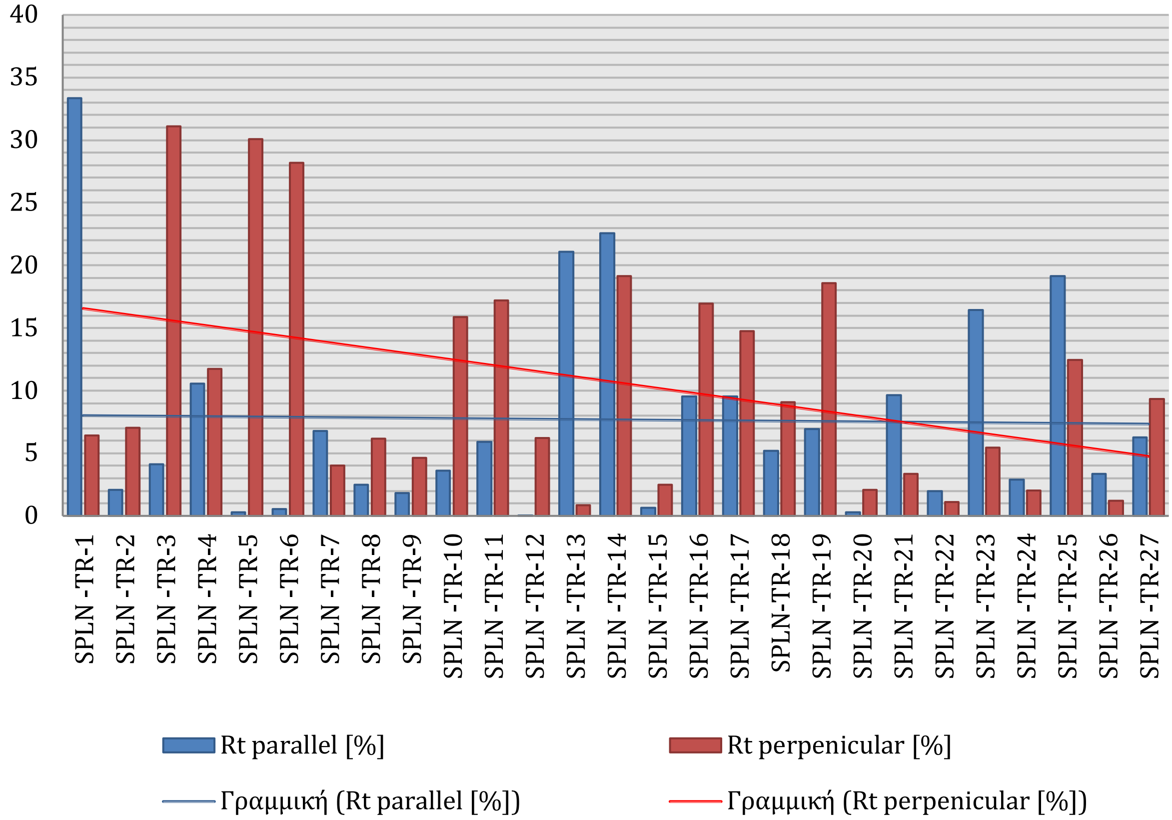


Figure 14. Graphical representation of the percentage error diagram for the approximate values Rt.

Following the graphical illustration of the error percentages in figure 14, a constant can be observed in the approximation of values Rt measured perpendicularly, as well as in the approximate values Rt measured in parallel.

4. Conclusions

The research and data modeling plan starts from the measurements, 3 measurements for each surface performed parallel to the feed direction and 3 measurements on each surface performed perpendicular to the feed direction. These measurements deserve as output neurons of the artificial neural network.

Data processing using MatLab software made it possible to create an artificial neural network, capable of approximating roughness values, having as input neurons the process variables during processing, and as output parameters the measured roughness.

With the creation and training of the artificial neural network it is able to learn the connections between neurons so as to generate new values of roughness.

These new values generated by the neural network for both the arithmetic roughness Ra and the total roughness Rt were compared with the real values. The comparisons resulted in a series of errors, the smallest error being 0.27% with a difference of 0.003 μm. This result certifies the adaptability of the neural network in generating new values of roughness.

5. References

[1] Golcu S, Semiz M, Ergur S and Aykut H S 2007 Modeling of cutting forces as function of cutting parameters for face milling of satellite 6 using an artificial neural network, Journal of Materials Processing Technology, vol. 190, pp. 199–203.
[2] Zuperl F and Cus U 2006 Approach to optimization of cutting conditions by using artificial neural networks Journal of Materials Processing Technology, vol. 173, pp. 281–290.
[3] Khani R A, Fakrabadi N, and Mahdavinejad S 2012 Optimization of milling parameters using artificial neural network and artificial immune system, Journal of Mechanical Science and Technology, vol. 26, pp. 4097-4104.
[4] Meenu A, 2013 Optimized Prediction and Modeling Under End Milling Machining By ANOVA And Artificial Neural Network , IJERT, vol. 2.
[5] Teti D and D'addona R, 2013 Image data processing via neural networks for tool wear prediction, Procedia CIRP, vol. 12, pp. 252 – 257.
[6] Celent D, Jozic L and Bajic S, 2012 Modeling of the Influence of Cutting Parameters on the Surface Roughness, Tool Wear and Cutting Force in Face Milling in Off-Line Process Control, Journal of Mechanical Engineering, vol. 58, pp. 673-682.
[7] Cus T, Paulic F, Balic M, and Irgolic J, 2014 Prediction of Cutting Forces with Neural Network by Milling Functionally Graded Material," Procedia Engineering, vol. 69, pp. 804 – 813.
[8] Rangajanardhaa GK, Hanumantha G, Rao G, Sreenvasa D, Rao M 2009 Development of hybrid model and optimization of surface roughness in electric discharge machining using artificial neural networks and genetic algorithm, J Mater Process Technol, vol. 209, pp. 1512–1520.
[9] Martinez-Blanco J, Vega-Carrillo E, Ortiz-Rodriguez H 2006 Robust design of artificial neural networks applying the Taguchi methodology and DOE, Proceedings of the Electronics, Robotics and Automotive Mechanics Conference, vol. 2, pp. 131–136.
[10] Ghoreishi S and Aaaarzadeh M 2008 Neural-network-based modeling and optimization of the electro-discharge machining process, Int J Adv Manuf Technol, vol. 39, pp. 488–500.
[11] Amin M, Patwari A and Hossain A 2008 Development of an artificial neural network algorithm for predicting the surface roughness in end milling of Inconel 718 Alloy, Roceedings of the International Conference on Computer and Communication Engineering, pp. 1321–1324.
[12] Mahapatra S and Panda S 2009 PCA fused NN approach fordrill wear prediction in drilling mild steel specimen, Proceedings of the 2nd IEEE International Conference on Computer Science and Information Technology, pp. 85–89.
[13] Oșan. A, 2019 Experimental Research on the Processing of Convex Spherical Surfaces with Toroidal Mills Versus Spherical Mills, Magazine of Hydraulics, Pneumatics, Tribology, Ecology, Sensorics, Mechatronics. Hidraulica, vol. 4.
[14] Oșan A, Bănică M and Năsui V 2019 The influence of inclination of the axis of the toroidal on a flat surface roughness. The 23nd edition of Innovative Manufacturing Engineering&Energy International Conference – ImanE&E 2019 Pitești vol 564.
[15] Oșan. A., Bănică. M. and Năsui. V. 2020 Processing of plane surfaces with toroidal milling versus ball nose end mill, Acta Technica Napocensis - Series: Applied Mathematics, Mechanics and Engineering, vol. 64.