International Journal of Modern Manufacturing Technologies
ISSN 2067–3604, Vol. XIV, No. 2 / 2022
https://doi.org/ 10.54684/ijmmt.2022.14.2.251

PRELIMINARY INVESTIGATION ON THE EFFECT OF CUTTING PARAMETERS ON SURFACE ROUGHNESS AND FLATNESS IN DRY MILLING OF PMMA

Florin Susac, Gabriel Radu Frumusanu

Dunarea de Jos University of Galati, Faculty of Engineering, Center of Excellence Polymer Processing,
111 Domneasca Street, 800201, Galati, Romania

Corresponding author: Gabriel Radu Frumusanu, gabriel.frumusanu@ugal.ro

Abstract: Polymethylmethacrylate (PMMA) also known as Plexiglass is a commonly used material for many applications, especially in medical industry. In some application, PMMA parts may be also used as molds for enabling fabrication of final products. Some of these parts are manufactured by injection molding, but in many cases mechanical machining of some surfaces is still required. The cutting of PMMA requires a previous optimization of the cutting parameters combination (feed rate and spindle speed). If this optimization is not carried out, the problems encountered may refer to cutting debris or material melting during machining and, consequently, the material attaches to the tool cutting edge. This will result in a surface with very poor quality, in terms of aspect and surface roughness. This paper reports on the preliminary experimental investigation of cutting parameters on the surface roughness and flatness error in dry milling of PMMA. The cutting experiments were conducted on EMCO MILL 55 CNC drilling and milling machine. The design of experiment (DOE) consists in L27 (33) design, meaning a three factorial experimental plan (3 factors on 3 levels). The cutting parameters, respectively depth of cut, feed rate and spindle speed are taken as inputs and surface roughness and flatness are taken as outputs. The surface flatness was measured with TESA Micro-Hite coordinate measuring machine. Analysis of variance (ANOVA) was adopted to identify the statistical influence of each input parameter and combination of input parameters on surface roughness. From the preliminary results, it can be observed that optimum regime is a combination of low feed rate, low depth of cut and high spindle speed. Moreover, an artificial neural model is proposed for prediction of surface roughness and flatness considering the depth of cut, feed rate and spindle speed as input variables. This approach aims to reveal the possibility of predicting the output parameters using neural network modelling, that can be further used to optimize the cutting regime.

Key words: PMMA, milling, surface roughness, ANOVA, cutting parameters, ANN, flatness error.

1. INTRODUCTION

In the last decades, polymers have been more and more used by many industries due to their properties such as low thermal conductivity, optical performance, and low cost [1]. Due to these excellent properties, polymethylmethacrylate (PMMA) has become the main material for micro-lens in fields of optics display, optic imaging, and communication [2]. At the same time, PMMA is very used in dentistry for its biocompatibility and convenient properties that refers to this material simple use [3].

PMMA is a main thermoplastic material with remarkable transparency. As concerning the thermal instability of PMMA, this makes it firmly restricted in being used for various applications [4].

For this reason, one of the main goals is to adopt the best strategy for preventing its degradation while machining. This strategy basis on modelling and optimization tools such as ANOVA analysis of variance and artificial neural networks for finding the optimum parameters that gives a good surface quality in accordance with quality goals.

The milling process is used in manufacturing biomedical components, aerospace, and automobile industries for making a wide range of parts from simple to complex geometry due to its capacity to rapidly remove material [5].

The machined surface quality is determined, along many other factors, by some process variables, the most important being feed rate, rotational speed, and depth of cut. To investigate the influence of these variables on surface quality and moreover to optimize the cutting process, many modelling techniques and methods [6,7] are used, such as Taguchi method [8-10], analysis of variance (ANOVA) [1,11] or artificial neural networks (ANN) [5,12,13]. Using these methods and techniques, several studies investigating the correlation between process variables and output quality are available in the literature.

ANOVA is used to identify the statistical influence of input variables on output parameters and ANN are used to connect inputs to outputs, based in experimental history, to predict data without performing additional time consuming and expensive experiments.

This paper presents a preliminary investigation on the effect of cutting parameters on surface roughness and flatness in dry milling of PMMA. The input variables are feed rate, rotational speed and depth of cut. By combining these three parameters, a three factorial experimental plan resulted. For each combination of the parameters, two outputs were investigated: surface roughness and surface flatness.

At the same time, the paper aims to reveal the possibility of predicting the output parameter by neural network modelling, that can be further used to optimize the cutting regime.

2. MATERIALS AND METHODS

2.1 Workpiece material and milling experiments

The machined material is polymethylmethacrylate (PMMA) that is commonly used in manufacturing components in computer and medical industries. Due to its high impact resistance, good machinability, scratch resistance, excellent transparency and good optical properties, this material can be used for manufacturing medical parts or machine cases.

The workpiece was supplied as rectangular plates of 150x50x15 mm. The general properties of this, Table 1:

Table 1. General properties of PMMA [14]

Properties	PMMA
Young modulus [MPa]	3200
Brinell Hardness	200
Density [kg/dm^3]	1.19
Melting temperature [°C]	160

Milling experiments were carried out on EMCO MILL 55 CNC drilling and milling machine (EMCO MAIER Ges. M.b.H. Austria), using a titanium milling tool. For each cutting parameters combination, a 50 mm linear channel was machined in attempt to study the resulted surface quality, in terms of surface roughness and surface flatness error. The scheme of the milling experiments is shown in Figure 1.

An experimental plan was designed to study the effect of cutting parameters on surface roughness and flatness error. The plan contains three factors (feed rate, rotational speed and depth of cut) at three levels, meaning 27 lines of parameters combination. The design of experiment is shown in Table 2.

The measurement of the surface roughness was carried out with a 2D profilometer (Mitutoyo Surftest SJ-210, Japan), equipped with Surftest SJ Communication Tool software. The flatness error was measured on TESA Micro-Hite coordinate measuring machine (MH3D, Tesa, Switzerland). For reliable roughness and flatness error values, the measurement was carried out five times and the average value of the measurements was reported and used in further analysis and prediction.

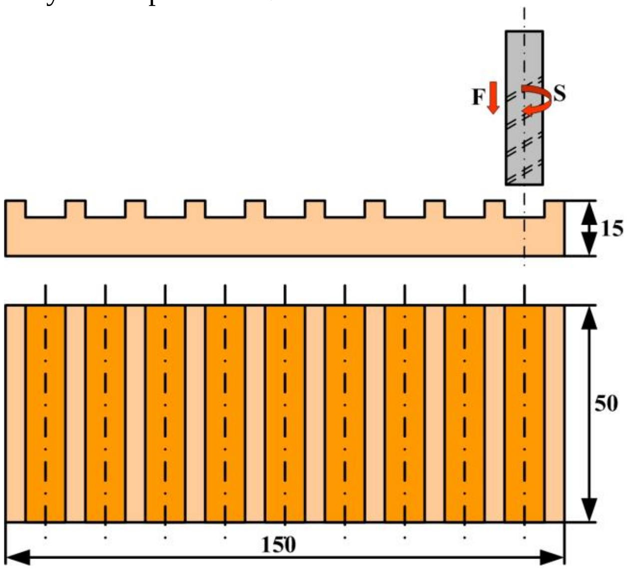


Fig. 1. Schematic view of milling experiments

Table 2. Design of experiment for surface roughness and flatness error prediction

Factors	Levels		
	1	2	3
Feed rate [mm/min]	300	900	1800
Spindle speed [rev/min]	1000	1800	3400
Depth of cut [mm]	0.08	0.14	0.24

2.2 Analysis of variance

The analysis of variance (ANOVA) was used to identify the statistical influence of each input parameter or combination of parameters on surface roughness. Prior to analysis of variance, the Anderson-Darling normality test was applied to check the normality hypothesis. The P-values lower than 0.05 shows that the effect of parameters is significant at 95% confidence level.

2.3 Artificial neural network model

The prediction of surface roughness and flatness error based on variation of cutting parameters (feed rate, rotational speed and depth of cut) was carried out using artificial neural network method. In this direction, MATLAB software was used to generate a neural model. Based on the experimental result, for both surface roughness and flatness error, neural model was generated, as shown in Figure 2.

The neural network was developed using trial-and-error method and consists in 3 layers: input layer with 3 neurons corresponding to input variables (feed rate, rotational speed, and depth of cut), hidden layer with 5 hidden neurons and output layer with 1 neuron corresponding to surface roughness, respectively flatness error. As it is already known from previous studies that a neural model has some limitations. One of the most important limitations is that other values of surface roughness can be predicted within the limits of minimum and maximum values of each parameter.

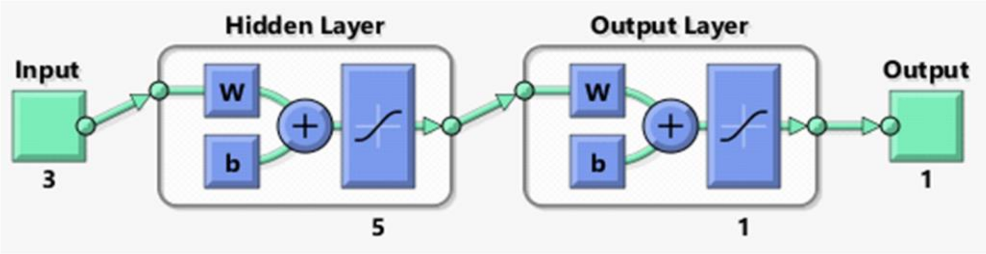


Fig. 2. Neural model for surface roughness and flatness error prediction

Anyway, there are mathematical methods for extrapolating for values out of min-max interval, but the accuracy of the resulting data depends on many conditions.

Table 3. Average experimental values of surface roughness and flatness error

Exp. no.	Feed rate [mm/rev]	Spindle speed [rev/min]	Depth of cut [mm]	Surface roughness [μm]	Flatness error [mm]
1	300	1000	0.08	1.747	0.007
2	300	1000	0.14	1.680	0.019
3	300	1000	0.24	1.526	0.037
4	300	1800	0.08	2.034	0.024
5	300	1800	0.14	1.885	0.025
6	300	1800	0.24	1.728	0.031
7	300	3400	0.08	1.548	0.013
8	300	3400	0.14	1.482	0.008
9	300	3400	0.24	2.312	0.015
10	900	1000	0.08	2.807	0.010
11	900	1000	0.14	3.068	0.013
12	900	1000	0.24	4.285	0.021
13	900	1800	0.08	2.486	0.026
14	900	1800	0.14	2.640	0.022
15	900	1800	0.24	2.433	0.019
16	900	3400	0.08	2.364	0.013
17	900	3400	0.14	2.354	0.011
18	900	3400	0.24	2.086	0.006
19	1800	1000	0.08	4.784	0.009
20	1800	1000	0.14	4.310	0.026
21	1800	1000	0.24	7.932	0.016
22	1800	1800	0.08	3.353	0.034
23	1800	1800	0.14	3.984	0.041
24	1800	1800	0.24	6.518	0.039
25	1800	3400	0.08	2.841	0.017
26	1800	3400	0.14	3.082	0.021
27	1800	3400	0.24	2.530	0.007

3. RESULTS AND DISCUSSION

The experimental results of the surface roughness and flatness error are presented in Table 3. Figure 3 shows the variation of surface roughness with respect to different milling conditions. It can be easily seen that an increasing of feed rate will increase the surface roughness. When machine with higher rotational speed, the resulting surface roughness will decrease. Finally, a high value of depth of cut will result in an increase of surface roughness.

If consider all three variables at the same time, it can be concluded that good results in terms of surface roughness can be reached if machining with low heed rate and depth of cut and high rotational speed. It is indicated to avoid a combination of high feed rate and low rotational speed that will result in high surface roughness.

A neural model generation is a complex problem because the experimental plan consists in a small number of experiments. For this reason, trail-and-error method was used in generation of the neural model. The final goal of this study was to identify the best neural model that accurately predicts surface roughness. The MATLAB software has a module especially developed for neural model generation. At the beginning, the software separated the experimental plan into three parts: 19 data sets were used for training and learning of the network, 4 instances were used for testing of the model and 4 instances were used for model validation.

From the beginning, it was assumed that a reliable neural model should assure a relative percentage relative error up to 5% and the neural model should have no more than 7 neurons on hidden layer to avoid overfitting.

The results of training, testing, and validating of the neural model are presented in Figure 4 for surface roughness and Figure 5 for flatness error. Moreover, a comparison between the experimental and predicted data is shown in Figure 6 for surface roughness and Figure 7 for flatness error, meaning the neural model ability to predict the target outputs.

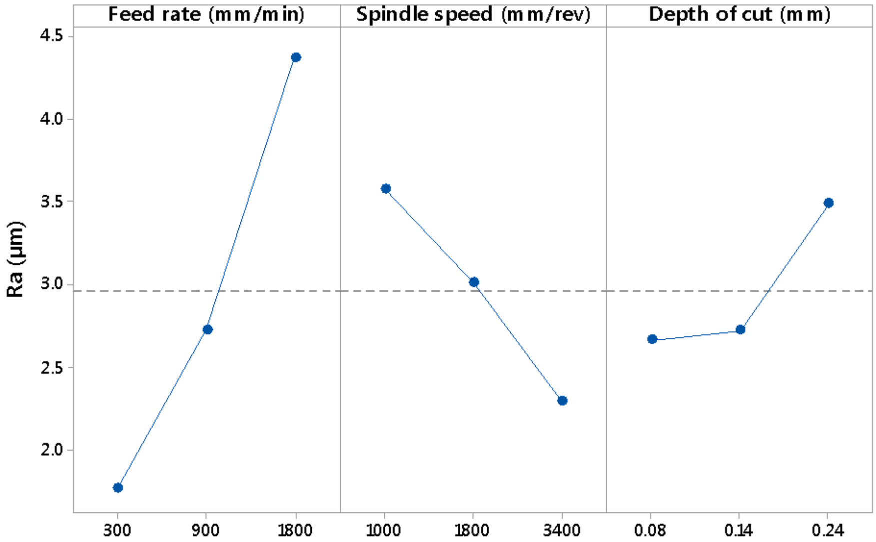
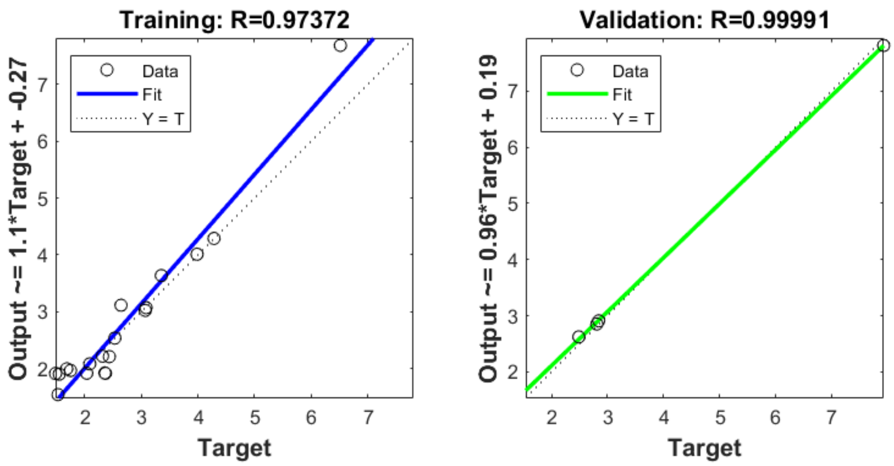


Fig. 3. Effect of milling parameters on surface roughness



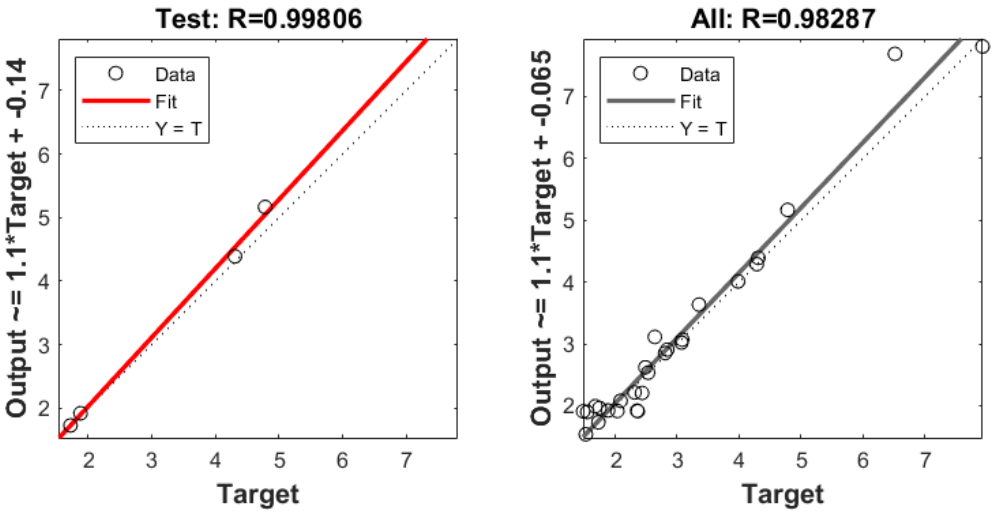


Fig. 4. Training, testing, and validating the neural model for surface roughness

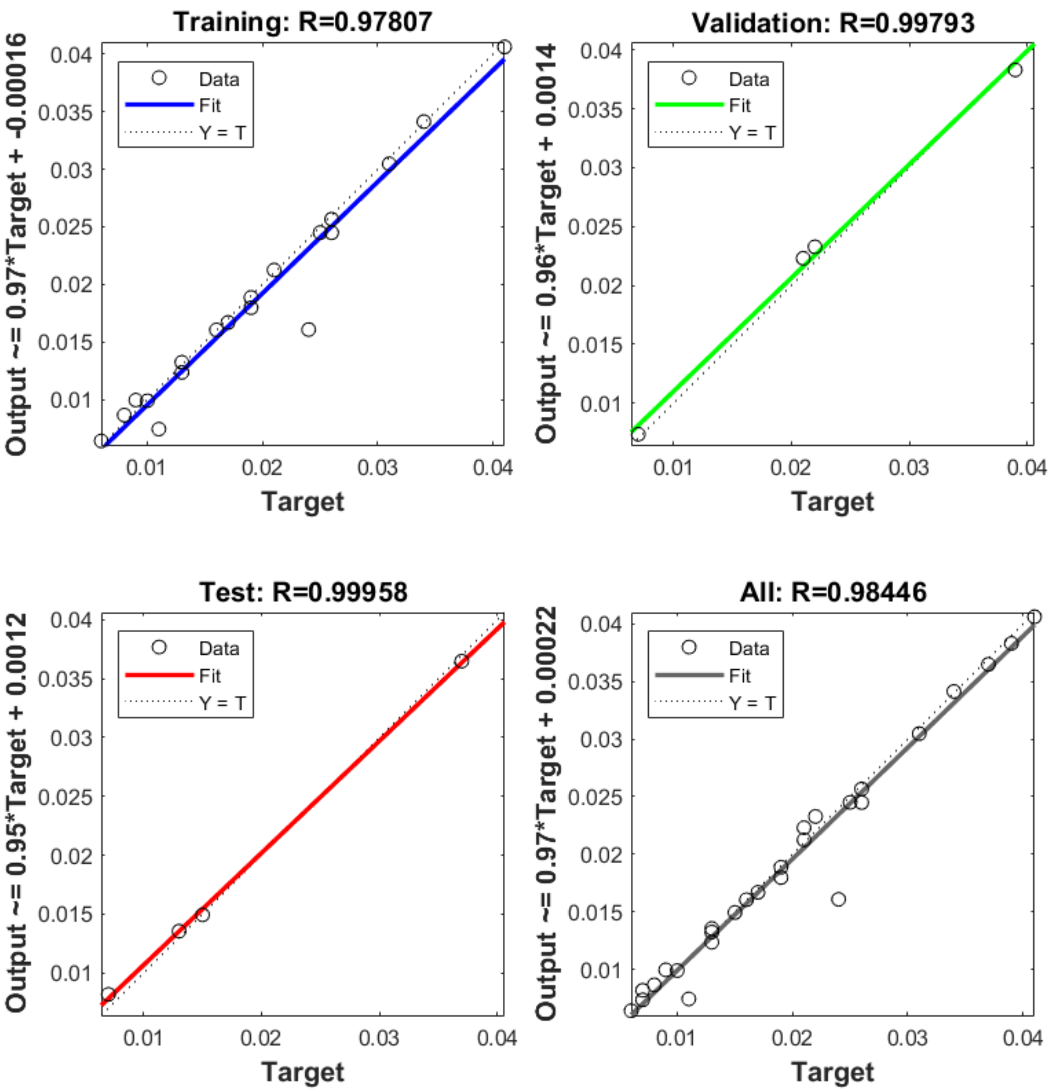


Fig. 5. Training, testing, and validating the neural model for flatness error

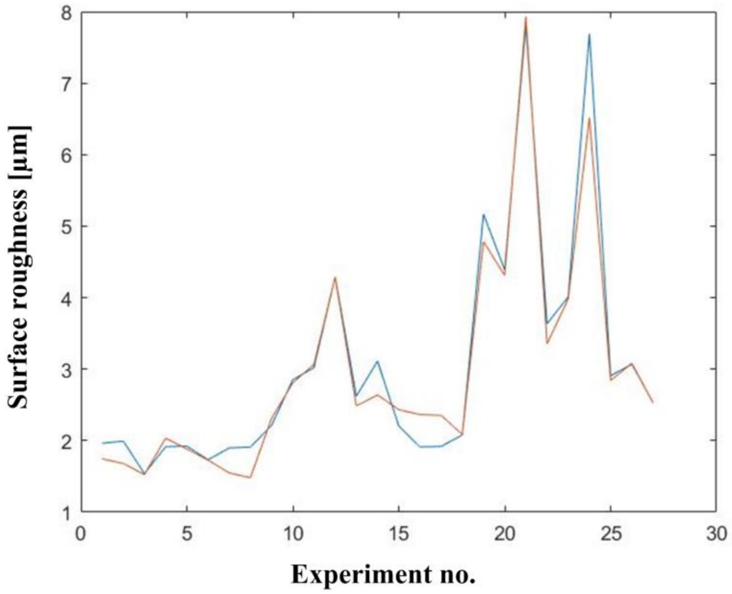


Fig. 6. Experimental vs. predicted data of surface roughness

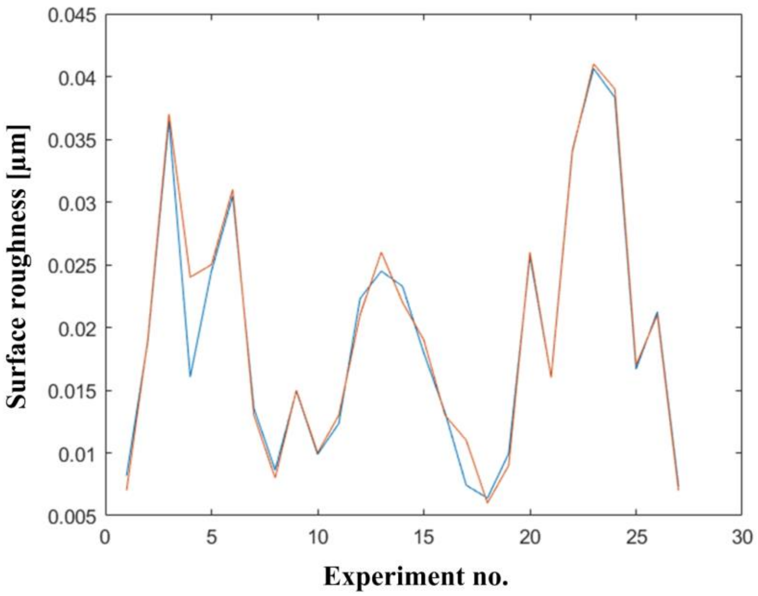


Fig. 7. Experimental vs. predicted data of flatness error

After prediction of surface roughness and flatness error were carried out, the relative errors between experimental and predicted data were calculated. It was found that the relative error between experimental and predicted surface roughness is 3.31% and the relative error between experimental and predicted flatness error is 0.02%. These two values of the relative error are reliable since it is considered that performant neural models should assure an average percentage relative error up to 5%.

4. CONCLUSIONS

In this study, milling experiments were conducted on PMMA to analyse the influence of cutting parameters (feed rate, rotational speed and depth of cut) on surface quality, in terms of surface roughness and flatness error. At the beginning, analysis of variance was carried out to identify the process parameters with significant influence on surface characteristics. Based on the experimental and predicted data, the following conclusions can be presented:

(i) The quality of the machined surface in dry milling, in terms of surface roughness, decreases with the increasing of feed rate and depth of cut and increase with the decrease of rotational speed. To machine high quality linear channel, it is recommended milling with low feed rate (300 mm/min), high spindle speed (3400 rev/min) and low depth of cut (0.08 mm).

(ii) The generated ANN model can predict with high accuracy the roughness and flatness of the milled surface with minimum relative error of the testing data of 3.31% for surface roughness and 0.02% for flatness error. These are acceptable values considering that the neural model has 1 hidden layer with 5 hidden neurons. The validation tests confirm the capability of the neural model to predict surface characteristics in dry milling of PMMA (in case of surface roughness, R2 = 0.9991 for validation and R2 = 0.9981 for testing and in case of flatness error, R2 = 0.9979 for validation and R2 = 0.9996 for testing).

5. REFERENCES

1. Korkmaz, E., Onler, R., Ozdoganlar, B., (2017). *Micromilling of Poly(methyl methacrylate, PMMA) using Single-Crystal Diamond Tools*, Procedia. Manuf., 10, 683.

2. Jiao, F., Cheng, K., (2013). *An experimental investigation on micro-milling of polymethyl methacrylate components with nanometric surface roughness*, Proc. Inst. Mech. Eng., Part B, 228(5), 790.

3. Chrysafi, I., Kontonasaki, E., Anastasiou, A.D., Patsiaoura, D., Papadopoulou, L., Vourlias, G., Vouvoudi, E., Bikiaris, D., (2020). *Mechanical and thermal properties of PMMA resin composites for interim fixed prostheses reinforced with calcium β-pyrophosphate*, J. Mech. Behav. Biomed. Mater., 112, 104094.

4. Patil, M.T., Lakshminarasimhan, S.N., Santhosh, (2021). *Optical and thermal studies of host Poly (methyl methacrylate) (PMMA) based nanocomposites: A review*, Mater. Today: Proc., 46, 2564.

5. Parmar, J.G., Dave, K.G., Gohil, A.V., Trivedi, H.S., (2021). *Prediction of end milling process parameters using artificial neural network*, Mater. Today: Proc., 38, 3168.

6. Baroiu, N., Teodor, V.G., Berbinschi, S., Susac, F., Oancea, N., (2016). *Optimizing Multiple Quality Characteristics of Stereolithography Process via Taguchi Method-based Grey Analysis for SL5530 Epoxy Resin Material to Enhance Part Quality*, Indian J. Eng. Mater. Sci., 23(5), 357.

7. Baroiu, N., Berbinschi, S., Teodor, V. G., Oancea, N., (2012). *The Modeling of the Active Surfaces of a Multi-Flute Helical Drill with Curved Cutting Edge Using the SV& Toolbox Environment*, Proc. 13th Int. Conf. Tools.

8. Kamaruddin, S., Khan, Z.A., Wan, K.S., (2004). *The Use of the Taguchi Method in Determining the Optimum Plastic Injection Moulding Parameters for the Production of a Consumer Product*, J. Mekanikal, 18, 98.

9. Fraley, S., Oom, M., Terrien, B., Zalewski, J., (2022). *Design of Experiments via Taguchi Methods - Orthogonal Arrays*, LibreTexts.

10. Raju, B.S., Chandra Sekhar, U., Drakshayani, D.N., (2014). *Optimizing Multiple Quality Characteristics of Stereolithography Process via Taguchi Method-based Grey Analysis for SL5530 Epoxy Resin Material to Enhance Part Quality*, Proc. Mat. Sci., 5, 2532.

11. Sreenivasulu, R., Srinivasa Rao, C., (2018). *Optimization of Machining Parameters During Drilling by Taguchi Based Design of Experiments and Validation by Neural Network*, Braz. J. Oper. Prod. Manag., 15, 294.

12. Leone, C., Matarazzo, D., Genna, S., d D'Addona, D.M., (2019). *A cognitive approach for laser milled PMMA surface characteristics forecasting*, Opt. Laser. Technol., 113, 225

13. Baroiu, N., Costin, G.A., Teodor, V.G., Nedelcu, D., Tabacaru, V., (2020). *Prediction of Surface Roughness in Drilling of Polymers Using a Geometrical Model and Artificial Neural Networks*, Mater. Plast., 57(3), 160.

14. Technical properties of PMMA; Available from: www.ceproinv.ro, Accessed: 07/04/2022.

Received: July 27, 2022 / Accepted: December 15, 2022 / Paper available online: December 20, 2022