Optimization of Machining Parameters to Minimize Surface Roughness in the Turning of Carbon-Filled and Glass Fiber-Filled Polytetrafluoroethylene

Muhammet Emre Sanci, Serdar Halis and Yavuz Kaplan

1 Introduction

Surface roughness is an important characteristic in industrial applications and involves friction, lubrication, heat transmission, corrosion resistance and wear. It is acknowledged that surface roughness determines the longevity and reliability of machine parts. Surface roughness is also an indicator of the amount of energy and other resources consumed during machining [1–5]. Thus, the determination of surface roughness is an essential factor in industrial applications.

One of the best thermoplastic polymers is Polytetrafluoroethylene (PTFE), which exhibits high thermal stability as well as good chemical resistance and dielectric properties. Because of its excellent mechanical properties and low friction coefficient, PTFE is the preferred engineering plastic for many applications and processing techniques. It is used in the production of seals, bearings, O-rings, electrical insulators, valve bodies and laboratory instruments requiring chemical resistance. Additionally, it is used in non-stick surfaces, engine parts, and for applications in the biotechnology and medical fields. At the same time, PTFE is used to coat automotive parts such as clutches, valves, etc. [6–9].

Glass fiber and carbon fillers can increase the mechanical properties of PTFE. However, fillers can lead to machining difficulties. Polymer composites differ from metals during machining processes owing to the time–temperature dependence of

M.E. Sanci (✉)
Department of Mechatronics Engineering, Pamukkale University, Denizli, Turkey
e-mail: msanci@pau.edu.tr

S. Halis
Department of Automotive Engineering, Gazi University, Ankara, Turkey
e-mail: serdarhalis@gazi.edu.tr

Y. Kaplan
Department of Manufacturing Engineering, Pamukkale University, Denizli, Turkey
e-mail: ykaplan@pau.edu.tr

L.F.M. da Silva (ed.), *Materials Design and Applications*,
Advanced Structured Materials 65, DOI 10.1007/978-3-319-50784-2_22

the polymers and additional structural fillers. The quality of a machined surface can be determined by taking into account the parameters of surface roughness, cutting speed, feed rate and depth of cut. Good machinability and superior product quality with minimum surface roughness values can then be obtained [1, 10].

Artificial neural networks (ANNs) are artificial intelligence nonlinear mapping systems that can solve problems of modeling and predicting experimental data. An ANN is commonly designed in a multi-layer form that includes an input layer, a hidden layer and an output layer. Jeyakumar et al. developed the response surface method (RSM) and ANN-based prediction models to determine the surface roughness of Al6061/SiC_p. The ANN model was found to perform better than the RSM model in determining the optimum machining parameters for minimum surface roughness [11].

In this study, an ANN-based prediction model was developed to determine the optimum cutting parameters (cutting speed, feed rate, and depth of cut) in terms of surface roughness in the turning of 25% carbon-filled and 25% glass fiber-filled PTFE. The performance of the ANN model was compared with the experimental results in order to determine its efficiency.

2 Materials and Methods

2.1 Measuring of Surface Roughness

The experiments were conducted using the MAHR MARSURF PS 1 mobile roughness-measuring instrument. The Korloy WNMG-NC5330 TiN-coated carbide insert was selected as the cutting tool. The machining parameters included two cutting speeds (150 and 200 m/min), three feed rates (0.1, 0.2, and 0.3 mm/rev) and three depths of cut (1, 2 and 3 mm) and the response considered was the average surface roughness (Ra). The experiments were carried out using commercially available pure (unfilled) PTFE, 25% carbon-filled PTFE and 25% glass fiber-filled PTFE in the form of cylindrical specimens with a diameter of 50 mm. The values reported in the study were taken from readings at different points on the circumference of the workpiece samples.

2.2 Production of PTFE

The PTFE was supplied by the APAMEYA Company. The PTFE powder and filler materials were mixed mechanically in the extruder to produce cylindrical samples 50 mm in diameter, as shown in Fig. 1.

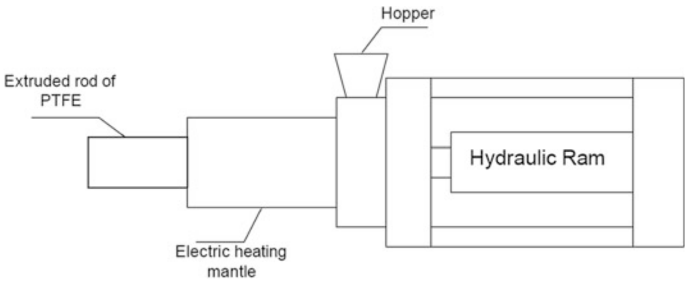

Fig. 1 Schematic illustration of PTFE sample production

2.3 Artifical Neural Network

The architectural approach was proposed to deal with the optimization of machining parameters in order to minimize surface roughness in the turning of carbon-filled and glass fiber-filled polytetrafluoroethylene. This approach is based upon nonlinear autoregressive models with exogenous input called NARX recurrent neural networks. The NARX model is one of the powerful class of models greatly suited for modeling non-linear systems, especially in time series. Control systems are one of the principal application fields of the NARX dynamic neural network, which contains recurrent feedback from several layers of the network to the input layer [12–14]. The architecture of the NARX neural network is given in Fig. 2.

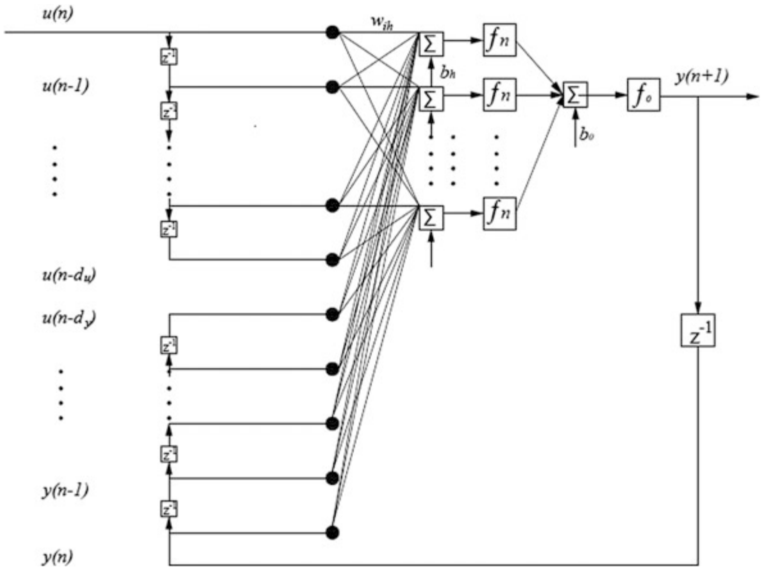

Fig. 2 Architecture of the NARX neural network

3 Results and Discussion

3.1 Experimental Results of Surface Roughness

The surface roughness tests were conducted on a CNC turning machine under dry conditions. The effect of feed rate and depth of cut on surface roughness in the turning of PTFE at a cutting speed of 150 m/min is shown in Fig. 3.

It can be seen that the surface roughness of pure (unfilled), 25% carbon-filled and 25% glass fiber-filled PTFE increases with the increase of feed rate in all depth of cut parameters. Therefore, an increasing feed rate resulted in higher surface roughness values, while a low feed rate was assumed to produce a better surface finish. In addition, the highest Ra value (4.4 μm) was observed on pure (unfilled) PTFE in turning at a feed rate of 0.3 mm/rev and a depth of cut of 3 mm. However, under these conditions, the effect of depth of cut on the surface roughness is very complex and it does not exhibit a regular behavior. Figure 4 presents a comparison of the surface roughness values of pure (unfilled), 25% carbon-filled and 25% glass fiber-filled PTFE.

Figure 4 reveals that the highest Ra values were obtained on pure PTFE in turning at all machining parameters. The lower Ra values were observed on carbon-filled and glass fiber-filled PTFE. This indicated that the carbon and glass fiber fillers led to a better surface finish with the preferred experimental parameters. In particular, the carbon fillers provided good machinability and superior product quality due to minimum surface roughness values. The effect of cutting speed on surface roughness in the turning of PTFE at a depth of cut of 1 mm is shown in Fig. 5.

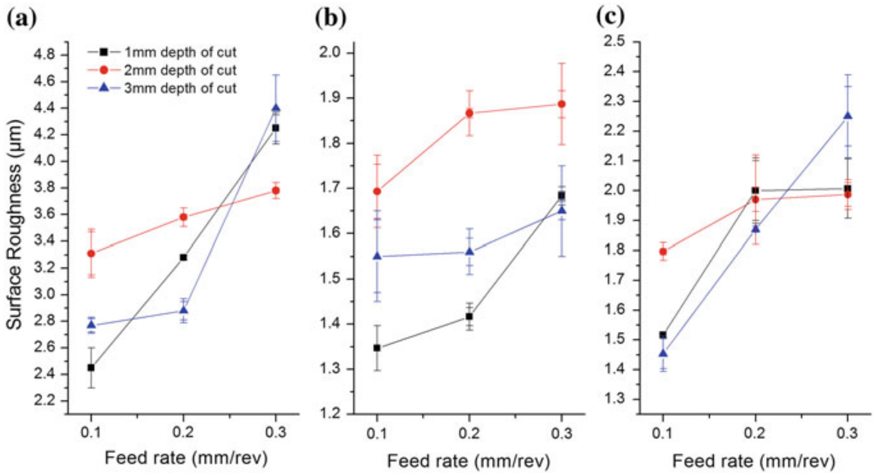

Fig. 3 Effect of feed rate and depth of cut on surface roughness in the turning of PTFE**: a** Pure (unfilled), **b** 25% carbon-filled, **c** 25% glass fiber-filled

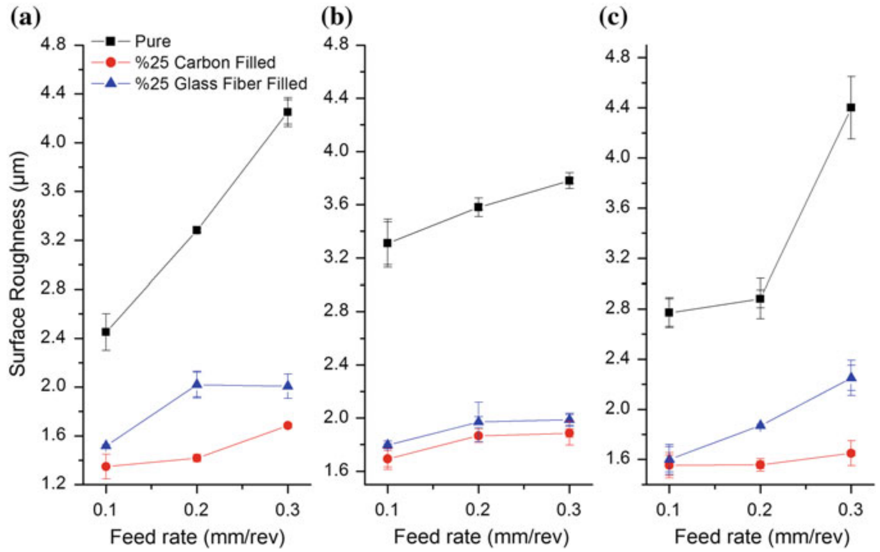

Fig. 4 Effect of feed rate and filled materials on surface roughness in the turning of PTFE: **a** 1 mm depth of cut, **b** 2 mm depth of cut, **c** 3 mm depth of cut

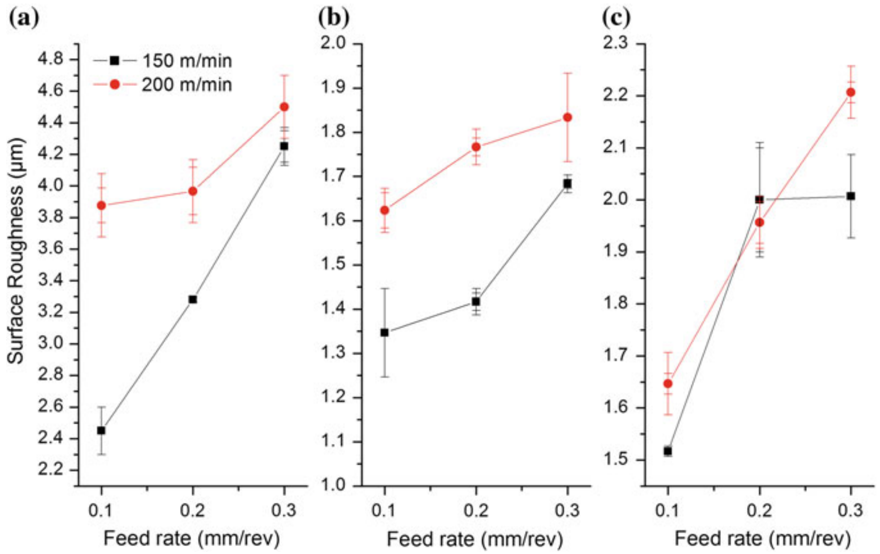

Fig. 5 Effect of feed rate and cutting speed on surface roughness in the turning of PTFE**: a** Pure (unfilled), **b** 25% carbon-filled, **c** 25% glass fiber-filled

It can be seen that the surface roughness values of pure, 25% carbon-filled and 25% glass fiber-filled PTFE generally decrease in all samples with the increase of cutting speed. Thus, a higher cutting speed resulted in lower surface roughness values, and a low feed rate was assumed to produce a better surface finish.

3.2 Comparison of ANN Predictions with Experimental Results

The dataset was taken from the experimental work in order to analyze the surface roughness during the turning of pure (unfilled), 25% carbon-filled and 25% glass fiber-filled PTFE. The MATLAB 2015 Neural Network toolbox with the NARX model was used for the experiments. The NARX network was capable of using multi-time series input and multi-time series output applications. In the current study, The Levenberg Marquardt (LM) algorithm, which is fast and consumes less memory [15], was used for training the algorithm.

The hyperbolic tangent sigmoid transfer function was used for activation of the function in the hidden layer as well as for the output layer. The learning algorithm used was the back propagation algorithm, which minimizes the total mean square error of the output computed by the network via a gradient-descent method. Data obtained from the experiments (machining parameters and surface roughness values) were used at the network learning stage. During network learning, the output of the network was compared with the desired output. The learning process is iterative and was stopped early to improve generalization by an increase in the mean square error of the validation samples. In sum, the data from 18 experimental trials were measured in order to build the neural network for each of the three experimental samples. In total, data from 54 experimental trials were used for the neural network modeling study, as shown in Table 1. It was necessary to decide on the number of neurons based on trial and error. This was accomplished by gradually increasing the number of neurons and observing the results of the change on the predicted values. As a result, the structure of the network was selected as 3-9-1 (Fig. 6). It included three input neurons in the input layer (corresponding to three machining parameters), one hidden layer with nine neurons and one output neuron in the output layer (corresponding to surface roughness).

No specific rule was employed for determining the number of data items to be used for training and for testing and validation; however, the general idea was that more data should be used for training than for testing and validation. Hence, 70% of the data was used for training, 15% for testing and another 15% for validation. The correlation coefficient (R-value) between the outputs and targets is a goodness-of-fit measurement of the variance between the outcomes and targets. The R-values of the validation data set shown in Table 2 indicate a strong correlation between the experimental outputs and the network outputs of the designed architecture of the ANN Ra prediction.

Table 1 Verification of the developed model with the experimental data

Experiment No.	Cutting speed (m/min)	Depth of cut (mm)	Feed rate (mm/rev)	Material	Surface roughness (μm)		Relative Error (%)
					Experimental	ANN model	
1	150	1	0.1	Pure (unfilled) PTFE	2.45	2.4	2.0408
2	150	1	0.2		3.28	3.51	−7.0122
3	150	1	0.3		4.25	4.18	1.6471
4	150	2	0.1		3.31	3.06	7.5529
5	150	2	0.2		3.58	3.41	4.7486
6	150	2	0.3		3.78	3.55	6.0847
7	150	3	0.1		2.77	2.62	5.4152
8	150	3	0.2		2.88	2.71	5.9028
9	150	3	0.3		4.4	3.9	11.3636
10	200	1	0.1		3.88	3.82	1.5464
11	200	1	0.2		3.97	4.23	−6.5491
12	200	1	0.3		4.50	4.13	8.2222
13	200	2	0.1		2.85	2.90	−1.7544
14	200	2	0.2		2.96	3.13	−5.7432
15	200	2	0.3		3.65	3.99	−9.3151
16	200	3	0.1		2.12	2.22	−4.7169
17	200	3	0.2		3.64	3.80	−4.3956
18	200	3	0.3		4.23	4.27	−0.9456
19	150	1	0.1	25% carbon-filled PTFE	1.35	1.41	−4.4444
20	150	1	0.2		1.42	1.57	−10.5634
21	150	1	0.3		1.68	1.67	0.5952
22	150	2	0.1		1.69	1.81	−7.1006
23	150	2	0.2		1.87	1.83	2.1390
24	150	2	0.3		1.89	1.82	3.7037
25	150	3	0.1		1.55	1.58	−1.9355
26	150	3	0.2		1.56	1.57	−0.6410
27	150	3	0.3		1.65	1.70	−3.0303
28	200	1	0.1		1.62	1.64	−1.2346
29	200	1	0.2		1.77	1.74	1.6949
30	200	1	0.3		1.83	1.74	4.9180
31	200	2	0.1		1.64	1.65	−0.6098
32	200	2	0.2		1.71	1.81	−5.8480
33	200	2	0.3		1.81	1.87	−3.3149
34	200	3	0.1		1.61	1.75	−8.6957
35	200	3	0.2		1.89	1.84	2.6455
36	200	3	0.3		2.05	1.94	5.3659

(continued)

Table 1 (continued)

Experiment No.	Cutting speed (m/min)	Depth of cut (mm)	Feed rate (mm/rev)	Material	Surface roughness (μm)		Relative Error (%)
					Experimental	ANN model	
37	150	1	0.1	25% Glass fiber-FILLED PTFE	1.52	1.49	1.9737
38	150	1	0.2		2.00	1.90	5.0000
39	150	1	0.3		2.01	1.96	2.4875
40	150	2	0.1		1.80	1.79	0.5556
41	150	2	0.2		1.97	1.86	5.5838
42	150	2	0.3		1.99	1.83	8.0402
43	150	3	0.1		1.60	1.64	−2.5000
44	150	3	0.2		1.87	1.94	−3.7433
45	150	3	0.3		2.25	2.44	−8.4444
46	200	1	0.1		1.65	1.82	−10.3030
47	200	1	0.2		1.96	1.92	2.0408
48	200	1	0.3		2.21	2.14	3.1674
49	200	2	0.1		1.93	2.02	−4.6632
50	200	2	0.2		2.04	2.02	0.9804
51	200	2	0.3		2.59	2.29	11.5830
52	200	3	0.1		1.90	1.82	4.2105
53	200	3	0.2		2.05	1.89	7.8049
54	200	3	0.3		2.62	2.48	5.3435

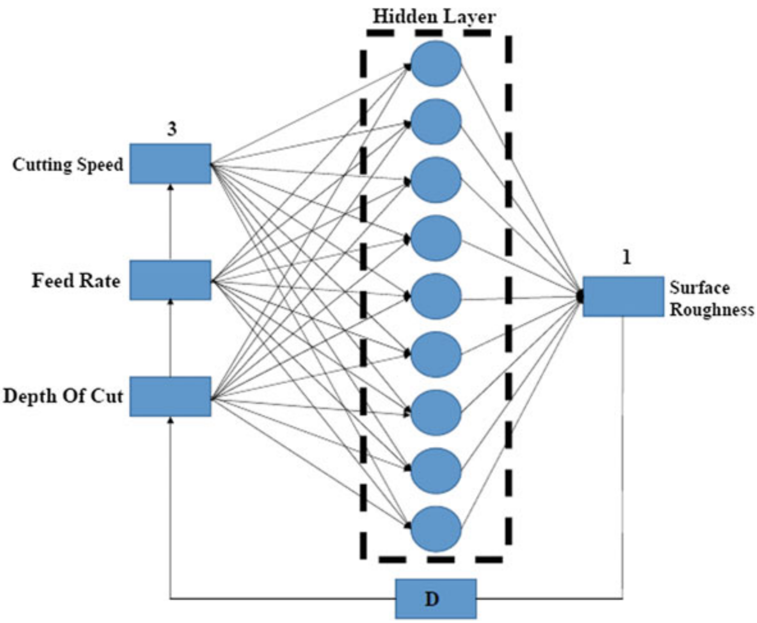

Fig. 6 Selected neural network architecture

Table 2 Correlation coefficients of validation datasets of the designed ANN

Cutting speed (m/min)	Pure (unfilled) PTFE	25% Carbon-filled PTFE	25% Glass fiber-filled PTFE
150	0.97	0.98	0.96
200	0.95	0.94	0.99

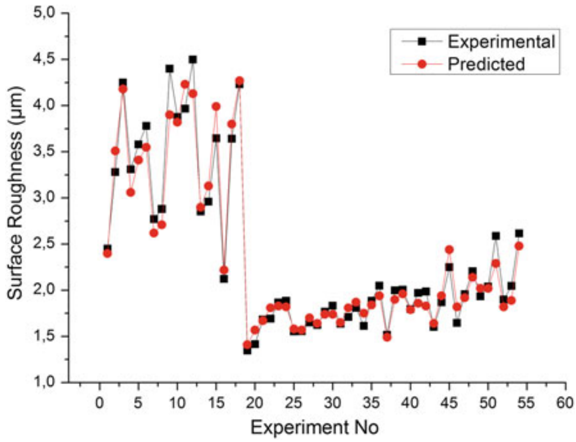

Fig. 7 Comparison of ANN results with experimental values

The predicted experimental data results are shown in Table 1. The average relative error between the experimental and predicted values was 4.66%. The average relative error between the experimental and predicted values together with the correlation coefficient of validation data (R-value) between the outputs showed that the well-trained network exhibited reliable accuracy in predicting the surface roughness values. Figure 7 shows the comparison of the ANN results with the experimental values. It can be seen that the neural network prediction results are very close to the experimental values.

4 Conclusion

An ANN-based prediction model was developed to determine the optimum cutting parameters (cutting speed, feed rate, and depth of cut) in terms of the surface roughness in the turning of 25% carbon-filled and 25% glass fiber-filled PTFE. In this study, in order to determine its efficiency, the performance of the ANN model was compared with the experimental results.

Differences between the average surface roughness values were observed after applying manufacturing parameters on pure (unfilled), 25% carbon-filled and 25% glass fiber-filled PTFE samples. It is generally recognized that feed rate is an important factor in the turning process of PTFE materials, and low cutting speed is believed to produce a better surface finish. Moreover, the effect of depth of cut on the surface roughness does not exhibit regular behavior. The lowest Ra value (1.35 μm) was obtained on the carbon-filled PTFE in turning at a cutting speed of 150 m/min, a feed rate of 0.1 mm/rev and a depth of cut of 1 mm, while the highest Ra value (4.4 μm) was observed on the pure PTFE in turning at a cutting speed of 150 m/min, a feed rate of 0.3 mm/rev and a depth of cut of 3 mm. Consequently, in the experiments, a better surface finish was obtained with the PTFE containing filler materials than with the unfilled PTFE.

When the ANN results were compared with the experimental values, the predictions of the neural network model were found to be accurate and reliable, with results very close to the experimental values. Thus, the proposed model can be used for prediction of the surface roughness in turning operations, with a promising potential for use in many other applications. The NARX model and Levenberg Marquardt (LM) algorithm were shown to be accurate for the optimization of the machining parameters.

References

1. Fetecau, C., Stan, F.: Study of cutting force and surface roughness in the turning of polytetrafluoroethylene composites with a polycrystalline diamond tool. Measurement **45**, 1367–1379 (2012)
2. Suresh, R., Basavarajappa, S., Gaitonde, V.N., Samuel, G.L.: Machinability investigations on hardened AISI 4340 steel using coated carbide insert. Int. J. Refract. Metal H. **33**, 75–86 (2012)
3. El-Gallab, M., Sklad, M.: Machining of Al/SiC particulate metal-matrix composites Part I: tool performance. J. Mater. Process. Technol. **83**, 151–158 (1998)
4. Kumar, R., Chauhan, S.: Study on surface roughness measurement for turning of Al 7075/10/SiCp and Al 7075 hybrid composites by using response surface methodology (RSM) and artificial neural networking (ANN). Measurement **65**, 166–180 (2015)
5. Sangwan, K.S., Saxena, S., Kant, G.: Optimization of machining parameters to minimize surface roughness using integrated ANN-GA approach. Proc. CIRP **29**, 305–310 (2015)
6. Akıncı, A., Akbulut, H., Yılmaz, F.: Floropolimer (Teflon) kaplamaların yapı ve özellikleri. UCTEA J. Chamb. Metall. Mater. Eng. **133**, 53–59 (2003)
7. Rooyen, L.J.V., Bissett, H., Khoathane, M.C., Kocsis, J.K.: J. Appl. Polym. Sci. (2016). doi:10.1002/app.43369
8. Li, F., Hu, K., Li, J., Zhao, B.: The friction and wear characteristics of nanometer ZnO filled polytetrafluoroethylene. Wear **249**, 877–882 (2001)
9. DuPont-Fluoroproducts: Teflon PTFE properties handbook: Tech. Rep. H-37051-3 (1996)
10. Karayel, D.: Prediction and control of surface roughness in CNC lathe using artificial neural network. J. Mater. Process. Technol. **209**, 3125–3137 (2009)
11. Jeyakumar, S., Marimuthu, K., Ramachandran, T.: Optimization of machining parameters of Al 6061 composite to minimize the surface roughness-modelling using RSM and ANN. Indian J. Eng. Mater. Sci. **22**, 29–37 (2015)
12. Leontaritis, I.J., Billings, S.A.: Input-output parametric models for nonlinear systems. Int. J. Control **41**, 303–344 (1985)

13. Ljung, L.: System Identification Theory for the User, 2nd edn. Prentice-Hall, Englewood Cliffs, New Jersey (1999)
14. Norgaard, M., Ravn, O., Poulsen, N.K., Hansen, L.K.: Neural Networks for Modelling and Control of Dynamic Systems. Springer, Berlin (2000)
15. Fausett, L.: Fundamentals of Neural Networks Architectures, Algorithms and Application. Prentice –Hall, New York (1994)