Optimizing Surface Roughness of Nylon6/$CaCO_3$ Nano-Composites Using Harmony Search Algorithm

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Abstract

Nowadays, polymer-based Nano-composites are of special importance in industry considering their mechanical properties including high strength to weight ratio. On another hand, since Nano-composites produced by methods such as extrusion are at simple cross sections, it is necessary to machine them in order to reach geometrically complex figures. Surface roughness is a parameter affecting mechanical specifications of the machined part. Thus, it is necessary to study surface roughness of the machined parts to reach optimized cutting parameters and optimized surface roughness. The present paper tries to experimentally test milling of Nylon 6/ $CaCo_3$ Nano-composites and measure surface roughness of the milled surfaces using the obtained data. The obtained data were used to model surface roughness to obtain an appropriate model for its milling. Finally, the obtained model was optimized using harmony search algorithm to reach optimized surface roughness and cutting parameters.

Keywords: Nano-composites, *harmony search algorithm*, *surface roughness*

1. Introduction

Surface roughness is an essential condition to study machinability of composite materials. Surface specification of polymeric materials is very important in some applications and is strongly affected by structure and composition of outer molecular layers. Appropriate surface quality is required for methods such as coating in order to reach special specifications such as hardness, wear and erosion resistance.

Although there are plenty of information about machining of metals, there is not sufficient information about machining of polymers and composites. During recent years, some studies have been conducted on machining performance of polymer composites. Farshbaf Zinati et al. [1] investigated the machining characteristics of Nylon 6/nano-calcium-carbonate using neural network models and analysis of variance (ANOVA). Rajmohan et al. [2] evaluated the drilling process of Al356/10SiC (Wt %) and hybrid composite of Al356/10SiC-3mica (Wt %) using three different drill tools. Mata et al. [3] modeled the cutting process of nylon66/glass fiber (30%) composite, physically. Davim and mata [4] studied the difference of the machinability of pure Nylon 6 and Nylon 6/glass-fiber composite using turning process. Dhokia et al. [5, 6] investigated the prediction and optimization of the surface roughness in ball-end machining of polypropylene. Davim et al. [7] compared the machining characteristics of pure Nylon 6 and Nylon 6/glass-fiber composite via precise turning. Farshbaf Zinati et al. [8] investigated the surface roughness and surface morphology of nylon6/multi-walled carbon nano-tube after end-milling process.

Modern industries mainly aims at manufacturing parts with the least cost, highest quality, and in the shortest time. Milling process is a widely-used technique in machining industry and finishing the surfaces. To manufacture parts with desired surface quality, the process parameters should be selected accurately because surface quality directly affects wearing and corrosion resistance properties. considering importance of surface roughness of all parts, several parameters such as spindle speed, feed speed, machine vibrations, tool material and geometry affecting surface roughness should be taken into account to have an appropriate and ideal surface roughness. However, there are some parameters such as set vibration which may not be measured exactly due to their nature and, thus, the results are not reliable. However, they may not be completely omitted, too. According to experiences, spindle speed and feed speed are those parameters highly affect surface roughness. considering subject of the study, i.e. surface roughness of Nano-composite, discussion of Nano-composites about compositions of composite materials and its filling particles, basis of composites in this study, i.e. Nylon 6, and using $CaCo_3$ to strengthen Nano-composite, weight percent of $CaCo_3$ on Nylon 6 was added to the important parameters (spindle speed and feed speed) to study these parameters and reach appropriate surface roughness.

2. Experimental Procedure

2.1. Material

The Nylon 6 with Brand of “Akulon, F232-D” from DSM company was used as matrix of the composites and the nano-CaCO3 particles of “Socal 312” from Solvay Company with good adhesion to Nylon 6 used as the filler of the composites. The polypropylene modified by maleic anhydride, was utilized to modify the adhesion among the polymer and nano-particles and increase the dispersion of the nano-particles in the polymeric matrix.

2.2. Tool and Machine Tool

The experiments were performed in a Deckel Maho DMU 70 V vertical axis computer numerical control (CNC) milling machine with a maximum spindle speed of 3,150 rpm and 3,000 mm/min maximum feed rate. The machine had a 5.5 kW spindle motor. The CNC part programs were created by employing TopSolid CAD/CAM software on a personal computer, Intel Pentium IV at 3.2 GHz.

2.3. Surface Roughness Measurement

Surface roughness tool of SURTRONIC 3+ from Taylor-Hobson Company was used to measure the surface roughness (Ra) in each experiment. To this end, three small regions on the machined surface were determined for measurements. The measurements in these regions were conducted, and the average value of three measurements was recorded as the Ra value. The tracing velocity and the sampling length were fixed at 0.5 mm/s and 0.8 mm, respectively.

2.4 Design of Experiments

In this study, different tests were done through full factorial design of parameters (spindle speed, feed speed, and weight-percent-content of CaCo3) such that 630, 1250, 2500rpm, 0.03, 0.07, 0.11mm/s, and 0%, 2.5%, 5%, 7.5%, and 10% were respectively considered for spindle speed, feed speed, and weight-percent-content of CaCo3. Doing so, 45 groups of experiments were done and surface roughness were separately obtained for each test.

3. Modeling via neural network

3.1 Back-Propagation Based Neural Networks

Neural networks simulate the human brain ability to learn the mathematical correlation between input and output parameters. It can model the relation between input and output parameters without using complex mathematical formulas. The knowledge of correlation between input and output parameters is transferred to network by a learning process based on experimental data. The method of applying the learning process is called learning algorithm. During the learning process, the synaptic weights of neurons are modified to approach a minimum difference between estimated output of NN and experimental output (Minimum error).One of the most frequently used learning algorithms in engineering applications, is Back-Propagation algorithm (BP). The BP is based on adjustment of neurons' weights using error back-propagation through the network from output to input layer.

3.2 Training data

Usually, 70-90% of all collected data are randomly selected as training data to be used in network training. In this study, 90% of data (40 groups) were selected for training to obtain a well-trained neural network. The values of three parameters (spindle speed, feed speed, and weight-percent-content of $CaCo_3$) were used as input and surface roughness as target in the network. The network is selected once it was trained by these data and it introduced the minimum error for the training data. The experimental data of surface roughness was listed in **table 1.**

3.3 Test data

Usually, 10-30% of all data are used to test the network. In this study, 10% of data (5 groups) which played no role in training process were used as input to the network. Output of the network was compared with real output and efficiency of the trained network was specified. The network with the least permitted error was confirmed, in comparison with other networks.

3.4 Correlating spindle speed, feed speed, and weight-percent-content of $CaCo_3$ to surface roughness by Neural Network

In current work, the NNTool of MATLAB was used to model the process. The trial and error method was used to obtain the optimum NN architecture. Doing this, various architectures with different number of neurons in each hidden layers were studied. After approximately 900 replications, 1-3-15-19 architecture was selected as the most appropriate one for surface roughness (figure 1).

This network has the lowest error in training and testing phases (Table 2).

Table .1. The experimental data

Test No.	Spindle speed (RPM)	Feed per tooth (mm/min)	$CaCO_3$ Content (%)	Surface Roughness; Ra (μm)	Test No.	Spindle speed (RPM)	Feed per tooth (mm/min)	$CaCO_3$ Content (%)	Surface Roughness; Ra (μm)
1	2,500	0.03	0	1.845	24	1250	0.11	5	6.863
2	2500	0.07	0	2.845	25	630	0.03	5	2.543
3	2,500	0.11	0	5.213	26	630	0.07	5	3.653
4	1250	0.03	0	2.112	27	630	0.11	5	6.273
5	1,250	0.07	0	3.132	28	2500	0.03	7.5	2.753
6	1250	0.11	0	7.435	29	2,500	0.07	7.5	3.243
7	630	0.03	0	2.232	30	2500	0.11	7.5	7.122
8	630	0.07	0	3.345	31	1,250	0.03	7.5	1.283
9	630	0.11	0	6.672	32	1250	0.07	7.5	2.193
10	2500	0.03	2.5	1.768	33	1,250	0.11	7.5	7.245
11	2,500	0.07	2.5	2.912	34	630	0.03	7.5	1.734
12	2500	0.11	2.5	6.788	35	630	0.07	7.5	4.325
13	1,250	0.03	2.5	2.301	36	630	0.11	7.5	7.222
14	1250	0.07	2.5	2.985	37	2,500	0.03	10	2.324
15	1,250	0.11	2.5	5.002	38	2500	0.07	10	3.653
16	630	0.03	2.5	2.014	39	2,500	0.11	10	7.435
17	630	0.07	2.5	3.234	40	1250	0.03	10	2.453
18	630	0.11	2.5	6.534	41	1,250	0.07	10	3.678
19	2,500	0.03	5	1.432	42	1250	0.11	10	6.365
20	2500	0.07	5	2.763	43	630	0.03	10	2.234
21	2,500	0.11	5	7.534	44	630	0.07	10	2.532
22	1250	0.03	5	2.563	45	630	0.11	10	4.176
23	1,250	0.07	5	2.654					

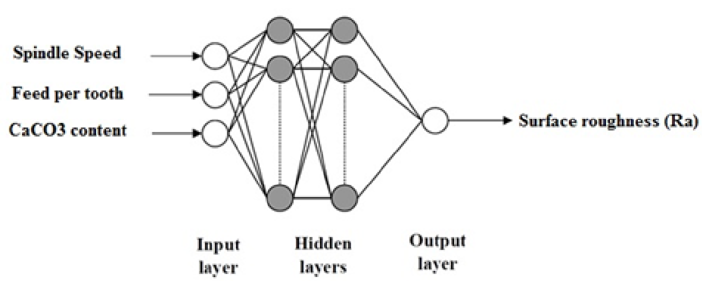

Fig. 1. The NN with two hidden layers and 1-3-15-19 architecture

Table. 2. Testing phase of trained NN

Input parameters			Output parameter		
Spindle speed (RPM)	Feed per tooth (mm/tooth)	$CaCO_3$ Content (%)	NN estimated Ra (μm)	Experimental Ra (μm)	Error (%)
2500	0.11	0	4.906	5.213	5.95
1250	0.11	2.5	6.080	5.002	21.5
630	0.03	5	1.710	2.543	32.0
630	0.03	7.5	1.901	1.743	10.38
1250	0.03	10	1.794	2.453	26.9

4. Optimization using harmony search algorithm

The harmony search algorithm was used to obtain the optimum combination of input parameters (weight percent of $CaCo_3$, spindle speed, feed speed) which results in optimum surface roughness. The MATLAB software was used to optimize the obtained neural network. The harmony search algorithm parameters were set as harmony memory size = 10, harmony memory size = 0.8, step adaptive rate = 0.4, bandwidth distance = XU-XL/1000, and number of improvements = 10000. The optimum result was listed in table 3.

Table 3 The values resulted from optimization

Spindle speed (RPM)	Feed per tooth (mm/tooth)	$CaCO_3$ Content (%)	Ra (μm)
848.6436	0.03	6.1864	0.5647

5. Conclusion

The present article studied effect of Nano-$CaCo_3$ content on milling of Nylon 6/ Nano-$CaCo_3$ composites and modelling of its machinability parameters using neural network. Surface roughness was studied using milling process of Nylon 6/ Nano-$CaCo_3$ composites and compared with pure Nylon 6.

Surface roughness was modeled using artificial neural network and optimized by harmony search algorithm. According to anticipations of neural network, the results were reliable in modelling of milling of Nylon 6/ Nano-$CaCo_3$ composites.

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