Prediction of Technological Parameters during Polymer Material Grinding

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Abstract: - This article introduces an application of artificial neural network with radial basis function in modeling of polymer materials grinding. This real technological process has many input parameters that influence results of grinding. In this paper the two key parameters were selected – feed rate and depth of cut. The task of the artificial neural network based predictor is to provide resulting surface roughness (Ra and Rz).

Key-Words: artificial neural networks, radial basis function, grinding, prediction

1 Introduction

Grinding is the finishing machining operation to ensure the final surface quality. Compared with the operation methods of defined tool geometry, a tool for grinding consists of a number of statistically oriented grinding grains of random shapes. During the grinding process, small chips are removed along with high rates of material removal. Therefore grinding operations are used for machining difficult-to and hardened materials. Grinding polymers, and in the case of this article predominantly thermoplastics, it is difficult due to their nature [7]. Despite this fact, grinding is widely used in the plastics industry for the clean-up of intake gates and overflows. The resulting surface quality depends on input factors such as principally cutting conditions are, followed by grinding material and accompanying phenomena [8, 9]. The choice of optimal cutting conditions in grinding is not as strongly influenced by the requirement of keeping the optimum tool life, as is the case with other machining methods.

Since grinding is mostly used as finishing method, which determines the functional properties of the surface, the knowledge of the surface quality and its control are crucial. It is therefore an effort to achieve high levels of surface quality; conditionally improved by the grinding process, choosing the appropriate cutting conditions. The quality of grinded surface is generally defined as the sum of the properties under consideration upon demands. It is a complex of system factors. Surface quality includes physical, chemical and geometric properties [10]. The geometric surface properties include roughness parameters as a characteristic of micro geometry in the cut plane perpendicular to the surface.

Artificial neural networks (ANNs) are commonly used for modeling of technological processes [1, 2, 3]. Typically multilayered feed-forward neural networks are utilized. However, these ANNs do not provide sufficient results in all applications. Therefore, it should be considered other types of artificial neural networks such as recurrent neural networks or neural networks with radial basis function (RBF). This paper focuses on application of the radial basis neural networks, because they offer very fast training and superior prediction accuracy.

2 Radial basis neural networks

Typical structure of radial basis neural networks contains two layers. As is depicted in the Figure 1, the hidden layer has radial basis function (RBF), whilst the linear transfer function is used in the output layer [4].

The radial basis function in the hidden layer is a function that normalizes radial distance between input vector $\mathbf{u}$ and the vectors formed from the rows of weight matrix $\mathbf{W}_1$. The bias vector $\mathbf{b}$ decides the range of influence of the particular RBF unit around its center defined in the matrix $\mathbf{W}_1$. General mathematical description of RBF networks is as follows [5]:

$$\mathbf{y} = S_2\,(\mathbf{b}_2 + \mathbf{W}_2\,\mathbf{x}_1) \quad (1)$$

$$\mathbf{x}_1 = S_1\,(\|\mathbf{u} - \mathbf{W}_1\|\mathbf{b}_1)\,, \quad (2)$$

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where **y** is the output vector of the network, $\mathbf{x}_1$ stands for the output vector of the hidden layer and S_i is transfer function of the i-th layer of the radial basis network.

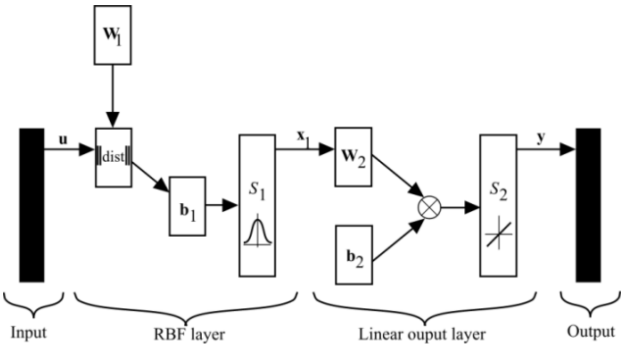

Fig. 1 - Schema of radial basis function neural network

Radial basis networks are popular for their fast training and adaptation. However, these positives bring some disadvantages. The main drawback of RBF network is high memory requirement, because in the classic approach the number of neurons in the hidden layer is equal to the number of training data. In the radial basis neural networks the weights $\mathbf{W_1}$ and biases $\mathbf{b_1}$ of the hidden layer are determined directly from the data. No training is involved. The weights $\mathbf{W_2}$ and biases $\mathbf{b_2}$ of the output layer are determined by supervised learning [6].

Table 1 - Physical and mechanical properties of polymer workpieces

	Modulus of Elasticity [MPa]	Ultimate Strength [MPa]	Melting Temperature [°C]	Hardness [Shore]
PP- Polypropylene	1500	27	170	70
PA6GF30- Polyamide 6 filled with 30% of glass fibres	7700	140	220	86
PTFE- Polytetrafluoroethylene	500	30	320	55
PC - Polycarbonate	2200	65	140	95

3 Methodology

For the experiment, polymer workpieces of block shape 50 x 50 x 20 mm were used from polypropylene (PP), polyamide 6 filled with 30% of glass fibres (PA6GF30), polytetrafluoroethylene (PTFE) and polycarbonate (PC) – details in Table 1.

Workpieces were attached to the surface grinding machine BRH 20.03F. Grinding wheel 99BA 46 J 9 V from sintered corundum with high porosity, that is recommended for polymer machining. Grinding was carried out with stroke back and forth, at specified cutting condition (Table 2) without cooling. For the preparation of experimental specimens, the depth of cut and feed rate was changed while the grinding wheel revolution was constant.

Prepared polymer specimens were measured using the stylus surface roughness tester Mitutoyo SJ-301 in the transverse direction to the feed rate vector. Measuring diamond tip radius was r_ε = 10 mm and measurements were made according to ISO 4287. For the purpose of this study, measurements were multiple repeated at the same conditions.

Table 2 - Conditions for the preparation of experimental specimens

Grinding wheel type	99BA 46 J 9 V
Grinding wheel size [mm]	250 x 20 x 76
Grinding wheel revolutions n_w [min^{-1}]	2550
Depth of cut a_e [mm]	0.01; 0.02; 0.03 and 0.04
Feed rate v_f [m/min]	8, 12, 16, 24

4 Results and discussion

The measured data were split into two parts. The first part was used for artificial neural network training, while the second group were processed and used as testing data for ANN verification. All mathematical computations were done in MATLAB and MATLAB Neural Network Toolbox.

Table 3 – Predicted values of *Ra* for PP

R_a [µm]	v_f [m/min]			
a_e [mm]	8	12	16	24
0.01	0.8990	0.8820	0.7450	0.9150
0.02	0.8130	0.9249	0.8360	0.9071
0.03	0.8060	1.0540	0.7981	1.0289
0.04	0.8480	1.0640	0.9090	1.1020
R_z [µm]	v_f [m/min]			
a_e [mm]	8	12	16	24
0.01	5.1112	4.9331	4.1012	5.1300
0.02	4.6160	4.9768	4.6177	4.9015
0.03	4.2691	5.7503	4.2865	5.4567
0.04	4.6751	5.9270	4.8060	5.9053

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There had to be created one ANN for each ground material. The predictor has two inputs (feed rate v_f and depth of cut a_e) and two outputs describing surface roughness (arithmetical mean roughness R_a and maximum height of the profile R_z). Predicted values for all materials are shown in tables 3 – 6.

Table 4 – Predicted results for PA6GF30

R_a [µm]	v_f [m/min]			
a_e [mm]	8	12	16	24
0.01	0.5889	0.6250	0.4490	0.5360
0.02	0.5320	0.5800	0.4850	0.5740
0.03	0.5640	0.5150	0.7290	0.5550
0.04	0.5320	0.4990	0.6250	0.5340
R_z [µm]	v_f [m/min]			
a_e [mm]	8	12	16	24
0.01	3.8125	4.0379	2.9893	3.3909
0.02	3.3337	3.6366	3.0759	3.6727
0.03	3.3390	3.3112	4.8340	3.4910
0.04	3.2867	3.0759	3.8360	3.3026

Table 5 – Predicted results for PTFE

R_a [µm]	v_f [m/min]			
a_e [mm]	8	12	16	24
0.01	0.3920	0.6040	0.5090	0.7180
0.02	0.5450	0.6290	0.5201	0.5280
0.03	0.5350	0.7810	0.6121	0.6500
0.04	0.6120	0.5640	0.6621	0.6500
R_z [µm]	v_f [m/min]			
a_e [mm]	8	12	16	24
0.01	2.2219	3.4180	2.7301	3.8990
0.02	3.0070	3.3401	2.8902	2.8369
0.03	2.9970	4.0399	3.3591	3.4941
0.04	3.4260	3.0200	3.5012	3.4659

After that, the predictors were subjected to verification using the second part of data. The verification data were statistically evaluated. Then, the mean values were computed for each combination of input parameters. These mean values (Figures 2-5) were compared to the predicted data.

As can be seen from figures, the predictors provide excellent predictions of desired output parameters for all tested polymers.

Table 6 – Predicted results for PC

R_a [µm]	v_f [m/min]			
a_e [mm]	8	12	16	24
0.01	0.6751	0.8590	0.5690	0.6660
0.02	0.6361	0.7680	0.7000	0.6860
0.03	0.7270	0.6520	0.7160	0.7470
0.04	0.9811	0.7990	0.8850	0.6820
R_z [µm]	v_f [m/min]			
a_e [mm]	8	12	16	24
0.01	3.5323	4.3191	3.1059	3.6260
0.02	3.1602	4.0151	3.6220	3.6770
0.03	3.6331	3.5331	3.7849	3.8320
0.04	4.7112	3.8961	4.7359	3.5511

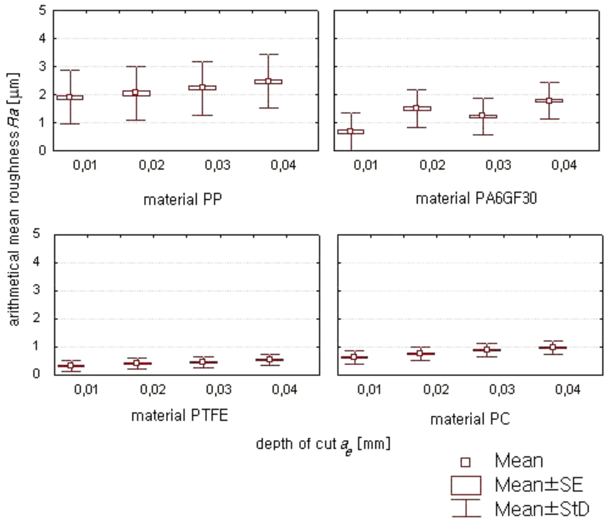

Fig. 2 - The dependence of R_a on the depth of cut a_e

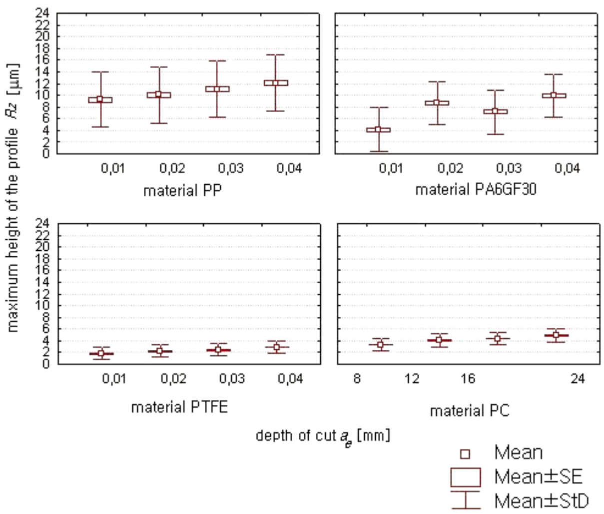

Fig. 3 - The dependence of R_z on the depth of cut a_e

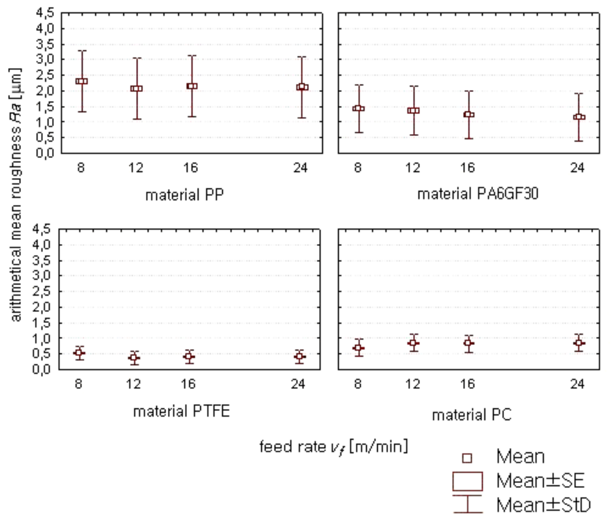

Fig. 4 - The dependence of roughness R_a on the feed rate v_f

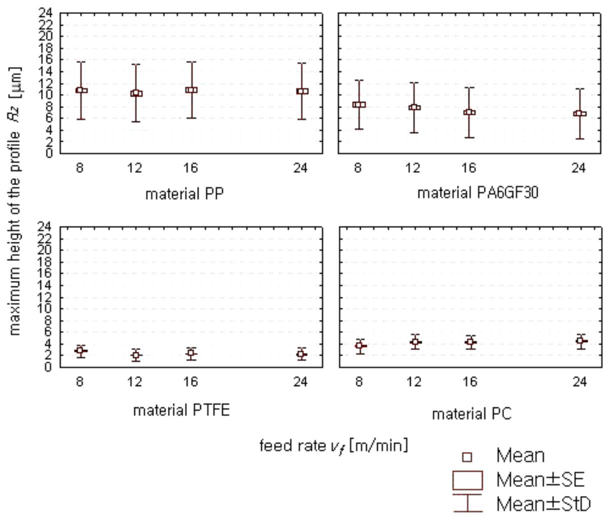

Fig. 5 - The dependence of roughness R_z on the feed rate v_f

4 Conclusion

This paper presented application of artificial neural networks to modeling of industrial process. The obtained predictions were even surprisingly good. It is probably caused by the nature of the real measured data. Because the data were very noised and obtained lot of outlaying values, it was necessary to use radial basis neural network that in this case produces approximately mean of the training data. This methodology has some drawbacks. One of them is mathematical dependency on the grinding material and used grinding wheel. This will be subject of the further research. It is assumed development of new model that would comprise the influence of the ground material and the grinding wheel properties.

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