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Prediction of surface roughness with genetic programming*

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In this paper we propose genetic programming to predict surface roughness in end-milling. Two independent data sets were obtained on the basis of measurement: training data set and testing data set. Spindle speed, feed rate, depth of cut, and vibrations are used as independent input variables (parameters), while surface roughness as dependent output variable. On the basis of training data set, different models for surface roughness were developed by genetic programming. Accuracy of the best model was proved with the testing data. It was established that the surface roughness is most influenced by the feed rate, whereas the vibrations increase the prediction accuracy.

1. INTRODUCTION

Survey of the hitherto researches about surface roughness reveals that particular efforts were devoted to the determination of as much as possible precise model for surface roughness prediction. A great part of the researches proposes the multiple regression method to predict surface roughness [1-3]. Some researches apply neural network, fuzzy logic, and neural-fuzzy approaches for surface roughness prediction [1, 4-6]. In most conventional deterministic approaches, such as multiple regression, a model for surface roughness prediction is determined in advance. Because of the prespecified size and shape of the model the latter is often not capable enough to capture complex relation between influencing parameters.

In this work we propose a genetic programming (GP) approach to predict surface roughness in end-milling. GP is evolutionary computation method which imitates biological evolution of living organisms [7-9]. Two independent data sets were obtained on the basis of measurement: training data set and testing data set. Spindle speed, feed rate, depth of cut, and vibrations are used as independent input variables, while surface roughness as dependent output variable. Different models for surface roughness were developed genetically on the basis of training data set. Prediction accuracy of the model was proved on the testing data set.

2. EXPERIMENTAL SETUP AND RESULTS

In this research experimental setup and a part of experimental results are based on the work of Lou [1]. In this section only the main points of this research are outlined.

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The experiment was performed by using CNC vertical machining center. The workpiece tested was aluminum cube of size L = 25.4 mm. The end-milling and four-flute high speed steel were selected as the machining operation and the cutting tool, respectively. The diameter of tool was D = 19.05 mm. Stylus type profilometer was used to obtain roughness average R_a as the value to express the surface finish. An accelerometer sensor was used to measure the vibrations. In order to get vibration voltage average value per revolution a proximity sensor was utilized to count the rotations of the spindle. Spindle speed (x_1), feed rate (x_2), depth of cut (x_3), and vibrations (x_4) were selected as independent variables.

Two sets of experimental data were obtained: training data set and testing data set. The training data set was obtained on the basis of four levels of spindle speed (750, 1000, 1250, and 1500 revolutions per minute), four levels of feed rate (152.4, 304.8, 457.2, and 609.6 millimeters per minute), and three levels of depth of cut (0.254, 0.762, and 1.27 millimeters). For each combination of spindle speed, feed rate, and depth of cut also the corresponding vibration data (in μV) were recorded. The corresponding value of the dependent output variable, i.e., roughness average R_a (in μm) was collected for each measurement. Table 1 shows a small part of the training data set. In this work training data comprised 120 measurements selected randomly out of 400 measurements originally presented in [1].

Table 1
Training data set

#	x_1 [min^{-1}]	x_2 [mm/min]	x_3 [mm]	x_4 [μV]	R_a [μm]
1	1500	152.4	127.0	1016.81	1.4224
2	1500	457.2	25.4	1358.05	3.048
3	1250	152.4	25.4	901.88	1.27
4	1000	609.6	25.4	1171.56	4.1402
5	1500	152.4	127.0	1053.35	1.4224
6	750	304.8	76.2	1278.61	2.5908
7	1500	609.6	127.0	1787.36	2.794
8	1250	609.6	76.2	2196.5	2.7686
⋮					
120	1000	609.6	127.0	1841.71	3.6068

The testing data set was obtained on the basis of four levels of spindle speed (750, 1000, 1250, and 1500 revolutions per minute), three levels of feed rate (228.6, 381.0, and 533.4 millimeters per minute), and three levels of depth of cut (0.254, 0.762, and 1.27 millimeters). Also for the testing data set the data on vibrations and surface roughness were recorded. The testing data set comprised 36 measurements (Table 2). Note that in Table 1 and Table 2 the depth of cut was calculated by multiplying the original depth of cut by the factor 100, and the vibration data were calculated by multiplying the original vibration data by the factor 10.000.

Table 2
Testing data set

#	x_1 [min^{-1}]	x_2 [mm/min]	x_3 [mm]	x_4 [μV]	R_a [μm]
1	1500	228.6	25.4	883.3	1.3462
2	1500	228.6	76.2	1110.07	1.8796
3	1250	228.6	25.4	1196.53	2.032
4	1250	228.6	76.2	1381.42	2.0828
5	1000	228.6	25.4	911.13	2.3368
6	1000	228.6	76.2	1225.66	2.4384
7	750	228.6	25.4	930.96	2.7686
8	750	228.6	76.2	1254.68	2.5146
⋮					
36	750	533.4	127.0	1658.57	3.81

3. CODING OF ORGANISMS AND FITNESS FUNCTION

The organisms that undergo adaptation are in fact mathematical expressions (models) for surface roughness prediction consisting of the available function genes (i.e., basic arithmetical functions, exponential function, power function, and sine function) and terminal genes (i.e., independent input variables, and random floating-point constants).

An average percentage deviation of all sample data for individual organism Δ was introduced as fitness measure. It is defined as:

$$\Delta = \frac{\sum_{i=1}^{n} \Delta_i}{n}, \tag{1}$$

where n is the size of sample data and Δ_i is a percentage deviation of single sample data. The percentage deviation of single sample data, produced by individual organism, is

$$\Delta_i = \frac{|E_i - G_i|}{E_i} \cdot 100\%, \tag{2}$$

where E_i and G_i are the actual R_a measured by a profilometer and the predicted R_a calculated by a model, respectively. It is assumed in this research that the problem is solved successfully if the average percentage deviation Δ of the model is less than 10%.

4. RESULTS

For all GP runs the evolutionary parameters were: population size 1000, maximum number of generations 300, probability of reproduction 0.1, and probability of crossover 0.9

4.1. Selection of genes

In order to establish which combination of the function and terminal genes best solves the set problem the introductory test runs of GP system were executed (for more detail about selection of genes see [10]). Analysis of the average percentage deviation of the best models showed that the probability of successful solutions is the greatest, if basic arithmetical functions (addition, subtraction, multiplication, and division) are used as the function genes.

The analysis of influence of the individual terminal gene on accuracy of the prediction of the surface roughness gave interesting results. In 5% of runs the evolution automatically eliminated either the variable depth of cut or vibrations from the developing model. The spindle speed and the feed rate variables always remained in the model. This implies that the spindle speed and, particularly, the feed rate are the most influencing parameters on which the surface roughness depends to the greatest extent. Consequently, the vibrations are not a quite independent variable and partly depend on the other three influencing variables. However, it was also unambiguously established that the presence of the vibrations as an independent variable considerably contributes to accuracy of prediction of surface roughness.

4.2. The Best Model

With the above mentioned genes, the simulated evolution in one GP run produced the following best model for prediction of surface roughness:

$$R_a = 2.68327 - \frac{(x_1 - 7.13018x_2)x_2}{x_1 x_4} - 2\frac{x_3}{x_1} + \frac{7.13018x_2(7.13018 - x_4 + 2x_1 - x_2 - 2x_3)(7.13018x_2 + x_3)}{x_1^2(-x_1^2 + x_1x_2 + x_3)} +$$

$$\frac{-x_1 + \dfrac{x_4(x_4 + 14.2604x_2)}{x_2(-2x_1 + 8.13018x_2 + 3x_3)} + \dfrac{1}{x_3}\left(29.5207x_2 + \dfrac{x_1(-x_1^2 + 7.13018x_2 + x_1x_2)}{7.13018x_2^2 + x_1x_3}\right)}{7.13018x_2 + 3x_3}. \tag{3}$$

The model was obtained in generation 162 and has the average percentage deviation of the training data set Δ_{tr} = 7.44% and of the testing data set Δ_{ts} = 7.74%. The analysis of the terms of the model 3 shows that the constant 2.68327, produced spontaneously during the evolutionary process, is simply the approximate average value of the measured R_a (actual average value of the measured R_a of the training data set is 2.614295).

5. CONCLUSION

This paper proposes the genetic programming approach to predict surface roughness based on cutting parameters (spindle speed, feed rate, and depth of cut) and on vibrations between cutting tool and workpiece. Our conclusions can be summarized as follows: (1) prediction accuracy of surface roughness by genetically developed models is very good both for the training and testing data set, (2) feed rate has the greatest influence on the surface roughness, and (3) GP can automatically find out significance of the influence of the individual independent variable on surface roughness. The models that involve all three cutting parameters and also vibrations, give the most accurate predictions of surface roughness. Further researches based on evolutionary analysis will explore more precisely independent variables influence on surface roughness as well as their mutual dependence. In addition, we will perform optimisation (e.g., with genetic algorithm) of the models' floating-point constants after the end of the genetic programming run.

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