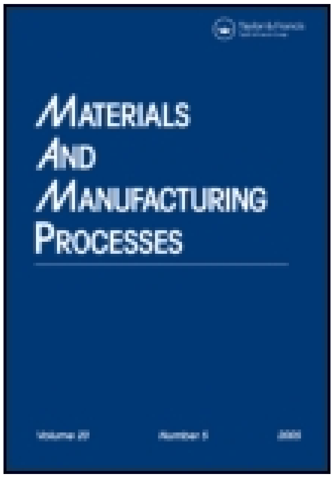

Materials and Manufacturing Processes
Publication details, including instructions for authors and subscription information:
http://www.tandfonline.com/loi/lmmp20

Integrated Genetic Programming and Genetic Algorithm Approach to Predict Surface Roughness

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Published online: 07 Feb 2007.

MATERIALS AND MANUFACTURING PROCESSES
Vol. 18, No. 3, pp. 475–491, 2003

Integrated Genetic Programming and Genetic Algorithm Approach to Predict Surface Roughness

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ABSTRACT

In this article we propose a new integrated genetic programming and genetic algorithm approach to predict surface roughness in end-milling. Four independent variables, spindle speed, feed rate, depth of cut, and vibrations, were measured. Those variables influence the dependent variable (i.e., surface roughness). On the basis of training data set, different models for surface roughness were developed by genetic programming. The floating-point constants of the best model were additionally optimized by a genetic algorithm. Accuracy of the model was proved on the testing data set. By using the proposed approach, more accurate prediction of surface roughness was reached than if only modeling by genetic programming had been carried out. It was also established that the surface roughness is most influenced by the feed rate, whereas the vibrations increase the prediction accuracy.

Key Words: Manufacturing systems; Surface roughness; Milling; Genetic programming; Genetic algorithm.

DOI: 10.1081/AMP-120022023
1042-6914 (Print); 1532-2475 (Online)

1. INTRODUCTION

Although we face expansion of modern technologies for machining of material, milling remains one of the most important machining processes. As in other manufacturing technologies, milled the surface roughness has a great influence on the functional properties of the product. It is well known that a high-quality milled surface significantly improves fatigue strength and corrosion resistance.[1,2] In addition, surface roughness also affects surface friction, light reflection, ability of holding a lubricant, electrical and thermal contact resistance, appearance, cost, etc. If the quality of the surface after milling is high, then further machining of the surface is frequently not necessary. In this way, the power consumption and the environment loading are decreased. These facts imply that good knowledge of the parameters determining the surface roughness and its precise prediction are very important. The influencing parameters can be divided into controlled and non-controlled parameters. The most important controlled cutting parameters are the spindle speed, feed rate, and depth of cut. However, there are many non-controlled cutting parameters (e.g., vibrations, tool wear, machine motion errors, material non-homogeneity of both the tool and workpiece, chip formation) that are hard to reach and whose interactions cannot be exactly determined.

A survey of previous surface roughness research reveals that particular efforts were devoted to the determination of the most precise model for surface roughness prediction. Most of the research propose the multiple regression method to predict surface roughness.[1–3] In Ref.[4], a commercial tool was used for surface roughness prediction, whereas in Ref.[5] a statistical model for surface quality prediction in end-milling is introduced. Some research applied neural network, fuzzy logic, and neural-fuzzy approaches for surface roughness prediction.[1,6–8] Optimization of the surface roughness prediction model, developed by a multiple regression method, with genetic algorithm is presented in Ref.[9]. In most conventional deterministic approaches, such as multiple regression, a model for surface roughness prediction is determined in advance. Merely a set of coefficients has to be found. Because of the prespecified size and shape of the model, the latter is often not capable enough to capture a complex relation between influencing parameters.

In this work we propose a new integrated genetic programming (GP) and genetic algorithm (GA) approach to predict surface roughness in end-milling. Genetic programming and a genetic algorithm are evolutionary computation methods that imitate biological evolution of living organisms.[10] They differ mainly in the structures undergoing adaptation. In GP, the structure subject to adaptation is the population of hierarchically organized computer programs,[11,12] whereas in GA, for example, it is the population of binary coded string, real-valued vectors,[13,14] etc. Because both the GP and the GA are general optimization approaches, they have been successfully applied for solving many different problems (see for example Refs.[14–18])

To predict surface roughness, 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), whereas surface roughness is the dependent output variable. The GP module was used to form the basic shape of the model for surface roughness prediction on the basis of training data set. No assumptions about the model form and size were

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determined in advance, but they were left to the evolutionary process. To ensure the most accurate prediction, fine tuning (optimization) of the model floating-point constants was further implemented in the GA module. Finally, prediction accuracy of the model was proved on the testing data set.

For the article to be self-contained, the basic terms on milling and surface roughness are stated in Sec. 2. In Sec. 3, experimental setup and experimental results are presented. In Sec. 4, the main idea of the proposed integrated concept is given. The coding of the organisms, the evaluation of population, and the genetic operations used are also described. Section 5 shows the results obtained. Section 6 summarizes the main contributions of our research and gives guidelines for further work. In the Appendix, the training and the testing data sets are shown.

2. BRIEF INTRODUCTION TO MILLING AND SURFACE ROUGHNESS

In a milling process, material is removed from the workpiece by a rotating cutter. The milling operation can be classified into peripheral milling and end-milling.[19] Peripheral milling generates a surface parallel to the spindle rotation, whereas end-milling generates a surface normal to the spindle rotation. End-milling is the most common metal removal operation.

Regardless of the method of production, all surfaces have their own characteristics, which are referred to as surface texture.[19] Surface texture is the pattern of the surface deviates from a nominal surface. The deviations may be repetitive or random and may result from roughness, flaws, and waviness.[1] Therefore, the actual surface profile is the superposition of error of form, waviness, and roughness.

Surface roughness is defined as closely spaced, irregular deviations on a scale smaller than that of waviness. Figure 1 shows standard terminology and symbols to describe surface roughness. The profile p is the contour of any specified section through a machined surface on a plane that is perpendicular to the surface. Roughness width cutoff l (i.e., sampling length) is included in the measurement of average roughness height. The mean line m of the profile p is located so that the sum of the areas above the line (within the sampling length l) is equal to the sum of the areas below the line.

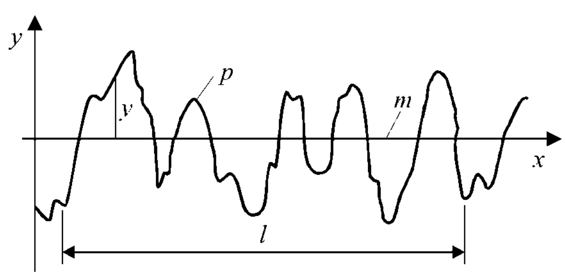

Figure 1. Surface roughness definition.

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Despite the different surface finish parameters, the roughness average R_a is the most used international parameter of surface roughness. It is defined as:

$$R_a = \frac{1}{l}\int_0^l |y(x)| \cdot dx, \tag{1}$$

where l is the sampling length, and y is the ordinate of the profile curve.

For inspecting a surface, several commercially available instruments, called surface profilometers, are used. The most commonly used instrument in practice is an amplified diamond stylus, which travels along a straight line over the surface. The distance that the stylus travels is sampling length l (Fig. 1); it generally ranges from 0.08 to 25 mm.[19]

Surface roughness is influenced by controlled machining parameters, such as feed rate, spindle speed, depth of cut, as well as by non-controlled influences, such as non-homogeneity of both the workpiece and the tool, tool wear, machine motion errors, formation of chips, and unpredictable random disturbances. It has been shown that both the controlled and the non-controlled parameters cause relative vibrations between the cutting tool and the workpiece. The correlation between surface roughness and cutting vibrations has also been demonstrated.[20]

The accelerometer is usually used to measure the surface vibrations. An accelerometer using a piezoelectric effect is very useful for their measurement. It is a property of piezoelectric materials that when they are under changing pressure (i.e., vibrating surface), an output voltage is generated by the material.

3. EXPERIMENTAL SETUP AND RESULTS

In this research, the experimental setup and some of the experimental results are based on the work of Lou.[1] In this section, only the main points of the experiment described in detail in the above-mentioned research are outlined.

The experiment was performed by using a CNC vertical machining center. The workpiece tested was a 6061 aluminum cube of size $L = 25.4$ mm (Fig. 2). The end-milling and four-flute high-speed steel were selected as the machining operation and the cutting tool, respectively. The diameter of the tool was $D = 19.05$ mm. Various spindle speeds, feed rates, and depths of cut were tested. During the machining, an accelerometer sensor was used to measure the vibrations. To get a vibration voltage average value per revolution, a proximity sensor was used to count the rotations of the spindle. Vibration voltage values and rotation signals were collected and converted into digital data by A/D board, which was connected with a personal computer. Finally, a stylus-type profilometer was used to obtain the roughness average R_a as the value to express the surface finish.

Spindle speed (x_1), feed rate (x_2), depth of cut (x_3), and vibrations (x_4) were selected as independent variables in this study. Vibrations depend partly on the other three independent variables, and thus the vibrations could be treated as a dependent variable. However, because of the complex structural system consisting of workpiece, fixture, cutting tool, and machine tool the vibrations and, consequently, the surface roughness cannot be described quite accurately by the limited set of

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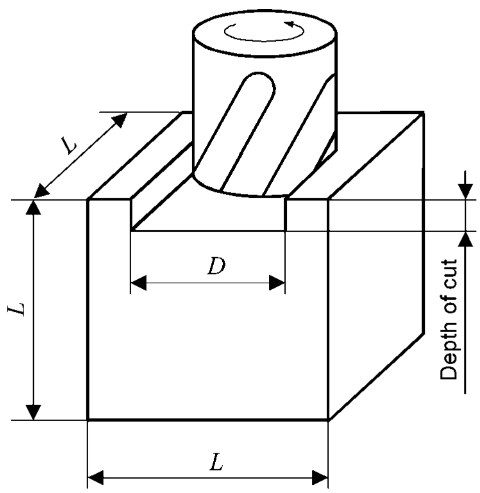

Figure 2. Workpiece.

independent variables. Therefore, for the time being, the vibration variable is treated as an independent variable. However, because in this research we use genetic programming as the primary approach, we expect that during the development of models the evolution automatically finds the influence of the individual variable on the surface roughness.

Two sets of experimental data were obtained: training (learning) 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 rpm), four levels of feed rate (152.4, 304.8, 457.2, and 609.6 mm/min), and three levels of depth of cut (0.254, 0.762, and 1.27 mm). For each combination of spindle speed, feed rate, and depth of cut, 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 A1 in the Appendix shows the training data set. In this work training data comprised 120 measurements selected randomly out of 400 measurements originally presented in Ref.[1].

The testing data set was obtained on the basis of four levels of spindle speed (750, 1000, 1250, and 1500 rpm), three levels of feed rate (228.6, 381.0, and 533.4 mm/min), and three levels of depth of cut (0.254, 0.762, and 1.27 mm). Also for the testing data set the data on vibrations and surface roughness were recorded. The testing data set comprised 36 measurements (Table A2 in the Appendix). Note that in Tables A1 and A2 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.

4. CONCEPT OF INTEGRATED GP-GA APPROACH

Our integrated GP-GA approach to predict surface roughness consists of two modules: the GP module and the GA module.

The GP module is intended for basic shaping of the model (see Subsec. 4.1). In the GA module, fine tuning of constants of the model, developed in the GP module, follows (see Subsec. 4.2). Our integrated GP-GA system is universal and is not limited to use in this research but is useful for any other problem where the experimental data on the process are available.

4.1. GP Module

In this module, the basic shaping of the model for surface roughness prediction is affected. Genetic programming is used. Figure 3 shows the main points of the procedure ***GP-module*** in pseudocode.

First, the initial population $P(t)$ of random organisms (i.e., models for prediction of surface roughness R_a) consisting of the available function and terminal genes is generated. The organisms are in fact computer programs of various shapes and sizes. The variable t represents the generation time. In this research, the set of function genes is represented by the basic arithmetical functions (operations of addition, subtraction, multiplication, division), power function, natural exponential function, and sine function. The latter two function genes have one argument each, whereas the other function genes have two arguments each. Terminal genes are in fact independent variables: spindle speed (x_1), feed rate (x_2), depth of cut (x_3), and vibrations (x_4). To increase genetic diversity of the organisms, the random floating-point numbers from the range [−10,10] are added to the set of terminals. Therefore, a randomly generated organism could have the following form:

$$7.3\frac{x_1}{x_3} + x_2x_4 - x_1 - 0.5.$$

The next step is the evaluation of the population $P(t)$. An average percentage deviation of all sample data for individual organism Δ was introduced as a fitness measure.

```
procedure GP-module
begin
 t ← 0
   initialize P(t)
   evaluate P(t)
   while (not termination_condition) do
   begin
      t → t + 1
      alter P(t) by applying genetic operators
      evaluate P(t)
   end
   procedure GA-module
 end
```

Figure 3. Evolutionary algorithm in GP module.

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It is defined as:

$$\Delta = \frac{\sum_{i=1}^{n} \Delta_i}{n}, \tag{2}$$

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 an individual organism, is

$$\Delta_i = \frac{|E_i - G_i|}{E_i} \cdot 100\%, \tag{3}$$

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. The smaller the values of Eq. 2, the better adaptation of the model to the experimental data.

Altering of the population $P(t)$ with genetic operations follows. Only reproduction and crossover were used. Figure 4 shows the operation of crossover. Two randomly selected parts of two parental organisms (in boldface) are interchanged. Thus, two offspring are created.

Evaluation and altering of population $P(t)$ are repeated until the termination condition has been fulfilled. This can be the prescribed maximum number of generations or sufficient quality of solution. Then the procedure ***GA-module*** is executed, where the optimization of constants of the model just obtained continues.

4.2. GA Module

This module is intended for fine tuning of the constants of the best model obtained from the GP module. A genetic algorithm was used. Figure 5 shows the main points of the procedure ***GA-module*** in pseudocode.

First, the initial population $P'(t)$ of real-valued vectors (organisms) is created randomly. The variable t is the generation time. The individual vector is equal to:

$$\boldsymbol{c} = (c_1, c_2, \ldots, c_j, \ldots, c_m), \tag{4}$$

where c_j is the individual constant (i.e., gene) in the model and m is the number of constants in the model. Therefore, the size of the vectors in population depends on the number of constants involved in the model developed during a genetic programming run. If the model does not contain any constants ($m = 0$), further optimization is not possible, and the final result is the model developed in the GP module. However, this occurs very rarely.

$$\frac{\boldsymbol{x_1 + x_2}}{5.6\,x_3} + x_1 x_3 \qquad\qquad \frac{(1 - x_2 x_3)}{5.6\,x_3} + x_1 x_3$$

Parent 1 Child 1

$$\xrightarrow{\text{Crossover}}$$

$$x_1(\boldsymbol{1 - x_2 x_3}) \qquad\qquad x_1(x_1 + x_2)$$

Parent 2 Child 2

Figure 4. Crossover of two mathematical expressions.

```
procedure GA-module
begin
 t ← 0
   initialize P'(t)
   evaluate P'(t)
   while (not termination_condition) do
   begin
      t → t + 1
      alter P'(t) by applying genetic operators
      evaluate P'(t)
   end
 end
```

Figure 5. Evolutionary algorithm in the GA module.

Evaluation of the population $P'(t)$ according to Eq. (2) follows. Note that in both the GP and the GA module, the fitness is calculated identically.

Altering of population $P'(t)$ is done by reproduction, crossover, and mutation. For crossover operation, two parental vectors are selected randomly. Then the crossover takes place between two randomly selected parental genes c_1 and c_2. Two offspring are created as follows:

$$c_1' = \frac{(\lambda_1 c_1 + \lambda_2 c_2)}{2}$$
$$c_2' = \frac{(\lambda_2 c_1 + \lambda_1 c_2)}{2}, \tag{5}$$

where λ_1 and λ_2 are random floating-point values from the range [0.9,1.1]. The number of crossover operations performed on each pair of parental vectors is selected randomly from the interval $[1, m]$. The mutation operation ensures fine tuning of the individual gene. In the mutation operation, one parental vector is selected randomly. Then, from one parental gene c, one offspring is created as follows:

$$c' = \lambda c, \tag{6}$$

where λ is the random floating-point value from the range [0.9,1.1]. Similarly, as in the crossover operation, the number of mutation operations performed on each parental vector is selected randomly from the range [1, m]. Evaluation and altering of population $P'(t)$ take place until the termination criterion has been fulfilled.

5. RESULTS AND DISCUSSIONS

5.1. Evolutionary Parameters

The evolutionary process in GP and GA modules was controlled by evolutionary parameters. Because of two different techniques, the control parameters in the

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GP module differ from those in the GA module. In this research, the same evolutionary parameters were used for all runs.

In the GP module, we selected the following evolutionary parameters: population size 1000, maximum number of generations to be run 300, probability of reproduction 0.1, probability of crossover 0.9, maximum depth for initial random organisms 6, and maximum permissible depth of organisms after crossover 15. The generative method for the initial random population was ramped half-and-half.[11] The method of selection for reproduction and crossover was tournament selection with a group size of 7.

In the GA module, the evolutionary parameters were population size 100, maximum number of generations to be run 200, probability of reproduction 0.1, probability of selection of organisms for crossover 0.5, and probability of selection of organism for mutation 0.4. The method of selection for all three genetic operations was tournament selection with a group size of 5.

5.2. Execution of Runs

The run starts in the GP module with the training phase on the basis of training data set shown in Table 1. The testing data set in Table 2 was not included within the training range. The evolution lasts up to the generation 100 when it is temporarily interrupted. If the average percentage deviation Δ of at least one model (organism) in the population is smaller than 10%, the evolution of the population continues up to generation 300; otherwise, it is terminated. The model, having the smallest average percentage deviation up to the generation 300, represents the input into the GA module where further optimization of the floating-point constants of the model just developed follows. Also during optimization of constants, only the data set for training is used. The optimization of constants takes place up to generation 200. In the end, the accuracy of prediction of the optimized model is tested with the testing data set.

5.3. Findings of Initial Runs

To establish which combination of the function and terminal genes best solves the set problem, the introductory test runs in the GP module were executed.

Four different combinations of function genes were basic arithmetical functions, basic arithmetic functions and natural exponential function, basic arithmetic functions and power function, basic arithmetic functions and sine function. In all four combinations of function genes the terminal genes (i.e., independent variables) were spindle speed, feed rate, depth of cut, and vibrations. Random floating-point constants were also added to the set of terminals. For each of the four combinations of function genes, several independent runs were executed. Analysis of the average percentage deviation of the best models showed that the probability of successful solutions is the greatest, if basic arithmetic functions (addition, subtraction, multiplication, and division) are used as the function genes. These genes were used in all subsequent runs.

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

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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 influential parameters on which the surface roughness depends to the greatest extent. Consequently, the vibrations are not quite an independent variable; they 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.

The introductory analysis of results shows that for developing the most accurate model, it is best to use the set of basic arithmetic operations and all four independent variables.

5.4. The Best Models

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

$$R_a = c_1 - \frac{(x_1 - c_2 x_2)x_2}{x_1 x_4} - 2\frac{x_3}{x_1} + \frac{c_2 x_2 (c_2 - x_4 + 2x_1 - x_2 - 2x_3)(c_2 x_2 + x_3)}{x_1^2(-x_1^2 + x_1 x_2 + x_3)} + \frac{-x_1 + \frac{x_4(x_4 + c_3 x_2)}{x_2(-2x_1 + c_4 x_2 + 3x_3)} + \frac{1}{x_3}\left(c_5 x_2 + \frac{x_1(-x_1^2 + c_2 x_2 + x_1 x_2)}{c_2 x_2^2 + x_1 x_3}\right)}{c_2 x_2 + 3x_3}, \tag{7}$$

where x_i is the individual independent variable and c_j is the floating-point constant. These constants developed during a genetic programming run can be presented in vector form as:

$$\boldsymbol{c} = (2.68327,\ 7.13018,\ 14.2604,\ 8.13018,\ 29.5207) \tag{8}$$

Therefore, the constants (i.e., coordinates) of the vector 8 are: $c_1 = 2.68327$, $c_2 = 7.13018, \ldots, c_5 = 29.5207$. The model (7) was obtained in generation 162 and has the average percentage deviation of the training data set $\Delta_{tr} = 7.44\%$ and of the testing data set $\Delta_{ts} = 7.74\%$. The analysis of the terms of the model (7) leads to a very interesting conclusion. The term $c_1 = 2.68327$, 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).

Then several optimizations of vector (8) in the GA module followed. The best solutions obtained after optimization are listed in Table 1 containing also the average percentage deviation Δ_{tr} and Δ_{ts} for the training and testing data set, respectively. Comparison of the results obtained after evolution in both modules with the results produced in the GP module only shows that additional optimization of constants improves the accuracy of the prediction. Because priority is given to the smallest possible error for the testing data set, the best solution of the problem is the genetically developed model (7) and the corresponding vector of constant #1 in Table 1. That solution has the average percentage deviation of 7.08% for the training data and 7.10% for the testing data.

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Table 1. The best solutions.

No.	Optimized vector of constants $\boldsymbol{c}$	Training Δ_{tr} [%]	Testing Δ_{ts} [%]
1	(2.68309, 6.91187, −24.1201, 12.8954, 38.0905)	7.08	7.10
2	(2.67798, 7.16851, −18.362, 12.8515, 25.2411)	7.20	7.42
3	(2.70374, 6.98879, 6.04615, 12.4664, 32.6536)	7.07	7.46

For this best solution, the percentage deviation of the single sample data for the training and testing data set are shown in Figs. 6 and 7, respectively. It can be seen that most deviations are considerably smaller than 10%.

The above results were obtained with population size 1000 and 100 in the GP module and the GA module, respectively. It can be expected that with greater population size, particularly in the GP module, the solutions would be even more precise.

6. CONCLUSION

This article proposes the integrated genetic programming and genetic algorithm 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:

- Prediction accuracy of surface roughness by genetically developed models is very good both for the training and testing data set.
- Basic shaping of the model is done in the GP module. Additional constants' optimization of the model in the GA module increases the prediction accuracy.
- Feed rate has the greatest influence on surface roughness.

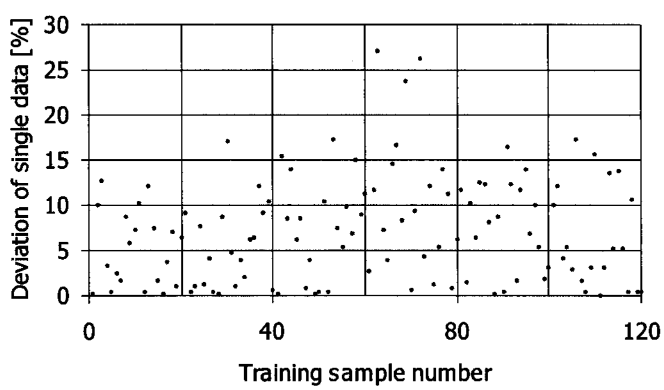

Figure 6. Percentage deviation of single sample data for training data set.

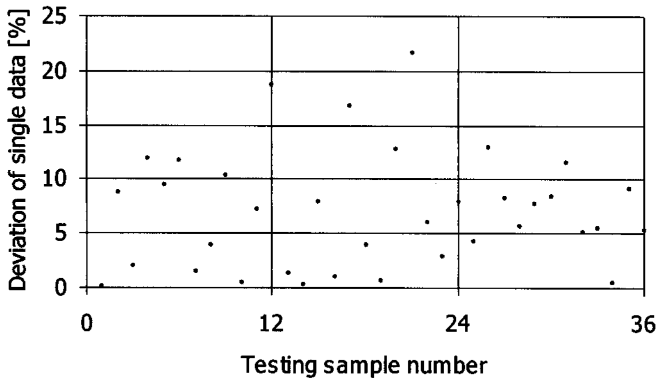

Figure 7. Percentage deviation of single sample data for testing data set.

- In the GP module, the evolution can automatically find the significance of the influence of the individual independent variable on surface roughness. If the influence is not decisive, it happens in some runs that evolution eliminates such a variable. However, the models that involve all three cutting parameters and vibrations give the most accurate predictions of surface roughness.

Further research based on evolutionary analysis will explore more precisely the independent variables' influence on surface roughness as well as their mutual dependence. In addition, we will perform optimization of the models' constants not only after the end of the evolution in the GP module but also during the genetic programming run (e.g., in every few generations). Therefore, the optimization in the GA module will be used as an additional genetic operation which, however, will be executed with relatively small probability.

APPENDIX

Table A1. Training data set.[a]

x_1 [min^{-1}]	x_2 [mm/min]	x_3 [mm]	x_4 [μV]	R_a [μm]
1500	152.4	127.0	1016.81	1.4224
1500	457.2	25.4	1358.05	3.048
1250	152.4	25.4	901.88	1.27
1000	609.6	25.4	1171.56	4.1402
1500	152.4	127.0	1053.35	1.4224
750	304.8	76.2	1278.61	2.5908
1500	609.6	127.0	1787.36	2.794
1250	609.6	76.2	2196.5	2.7686
1250	304.8	25.4	1303.71	2.54

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Table A1. Continued.

x_1 [min^{-1}]	x_2 [mm/min]	x_3 [mm]	x_4 [μV]	R_a [μm]
1000	609.6	127.0	1841.71	3.6068
1500	609.6	76.2	1909.07	2.6162
1250	457.2	25.4	1455.83	2.921
1500	457.2	25.4	1653.52	3.048
1500	609.6	25.4	1413.37	3.048
1500	304.8	25.4	1123.07	2.2352
1000	152.4	25.4	803.17	1.4732
1000	304.8	127.0	1759.27	2.3368
1500	457.2	127.0	1523.0	2.6416
1500	152.4	25.4	802.91	0.9398
1250	304.8	25.4	1447.97	2.54
1000	152.4	127.0	1029.08	1.5748
1000	152.4	25.4	830.36	1.4732
1250	609.6	127.0	1829.14	3.0734
1250	152.4	127.0	968.99	1.8034
1500	304.8	25.4	1038.26	2.2352
750	152.4	127.0	836.63	1.8288
1500	304.8	76.2	1205.49	2.0828
750	609.6	76.2	1688.99	4.3434
1500	457.2	25.4	1235.88	3.048
1000	304.8	25.4	881.66	3.302
1250	609.6	25.4	1182.19	3.9624
750	609.6	127.0	1544.99	4.3688
750	609.6	127.0	1705.2	4.3688
1250	457.2	25.4	1315.1	2.921
1500	152.4	76.2	1087.2	1.4224
750	304.8	127.0	1191.44	2.3876
1250	152.4	25.4	770.61	1.27
1000	152.4	127.0	1005.44	1.5748
1000	609.6	76.2	1807.41	3.8862
1250	304.8	127.0	1225.86	2.159
1500	152.4	127.0	911.31	1.4224
1250	457.2	76.2	1572.92	2.3368
1000	609.6	76.2	1685.56	3.8862
1000	152.4	76.2	1097.6	1.9812
750	609.6	25.4	1236.73	4.7498
1000	457.2	76.2	1725.19	3.1496
750	304.8	76.2	1423.14	2.5908
1000	304.8	127.0	1800.08	2.3368
1500	609.6	25.4	1987.12	3.048
1500	152.4	25.4	743.92	0.9398
750	609.6	25.4	1119.85	4.7498
1000	152.4	25.4	796.67	1.4732
750	304.8	25.4	991.03	3.6576
1000	457.2	76.2	1614.87	3.1496
1250	304.8	25.4	1217.03	2.54

(*continued*)

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Table A1. Continued.

x_1 [min^{-1}]	x_2 [mm/min]	x_3 [mm]	x_4 [μV]	R_a [μm]
1250	609.6	76.2	2102.66	2.7686
1000	609.6	76.2	1597.55	3.8862
1500	304.8	127.0	1237.45	2.3876
1500	609.6	76.2	2030.95	2.6162
750	457.2	25.4	930.08	4.699
750	304.8	76.2	1265.41	2.5908
1500	609.6	76.2	1789.84	2.6162
750	152.4	25.4	889.81	1.6764
1250	152.4	127.0	1105.54	1.8034
750	152.4	127.0	897.52	1.8288
1500	457.2	76.2	1499.63	2.2098
750	304.8	25.4	940.94	3.6576
1250	609.6	76.2	2242.47	2.7686
750	152.4	76.2	1010.99	1.6002
1000	152.4	25.4	781.31	1.4732
1000	609.6	127.0	2004.41	3.6068
750	152.4	25.4	1045.43	1.6764
1500	609.6	25.4	1621.89	3.048
1250	304.8	76.2	1488.66	2.5146
1500	304.8	25.4	1057.32	2.2352
1500	457.2	127.0	1346.65	2.6416
1500	457.2	76.2	1568.62	2.2098
1250	304.8	76.2	1320.09	2.5146
1500	152.4	25.4	638.19	0.9398
1000	609.6	127.0	1775.34	3.6068
1000	304.8	76.2	1479.68	2.1336
1250	609.6	127.0	1661.56	3.0734
1500	609.6	76.2	1903.95	2.6162
1500	457.2	127.0	1436.1	2.6416
1250	152.4	25.4	839.57	1.27
1250	152.4	25.4	790.13	1.27
1500	609.6	25.4	1379.26	3.048
1500	152.4	25.4	696.48	0.9398
750	457.2	76.2	1406.81	3.7338
1000	609.6	25.4	1264.34	4.1402
750	304.8	25.4	936.44	3.6576
1250	304.8	76.2	1554.73	2.5146
750	609.6	76.2	1792.84	4.3434
1250	304.8	76.2	1415.03	2.5146
1000	152.4	76.2	1103.1	1.9812
1000	609.6	127.0	1824.54	3.6068
1500	457.2	25.4	1359.04	3.048
1500	609.6	25.4	1547.65	3.048
1500	304.8	25.4	1190.46	2.2352
750	609.6	127.0	1652.85	4.3688
1500	457.2	25.4	1371.51	3.048

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Table A1. Continued.

x_1 [min^{-1}]	x_2 [mm/min]	x_3 [mm]	x_4 [μV]	R_a [μm]
1250	304.8	76.2	1487.23	2.5146
1000	304.8	127.0	1853.21	2.3368
1500	609.6	25.4	1547.63	3.048
1250	457.2	127.0	2191.82	2.413
1000	304.8	25.4	898.28	3.302
750	304.8	76.2	1357.69	2.5908
1250	152.4	76.2	1210.27	1.6002
750	304.8	76.2	1228.06	2.5908
1500	457.2	76.2	1400.02	2.2098
750	609.6	76.2	1678.78	4.3434
1000	304.8	127.0	1630.7	2.3368
1500	457.2	76.2	1616.45	2.2098
1500	609.6	25.4	1557.36	3.048
1000	152.4	76.2	1038.66	1.9812
750	304.8	127.0	1290.04	2.3876
1500	152.4	127.0	1081.28	1.4224
1500	457.2	25.4	1435.73	3.048
1500	152.4	127.0	1068.06	1.4224
1250	152.4	76.2	1238.22	1.6002

Depth of cut (x_3) = Original depth of cut × 100.
Vibrations (x_4) = Original vibrations × 10,000.
[a]The data shown are a part of the original data presented in Ref.[1].

Table A2. Testing data set.[a]

x_1 [min^{-1}]	x_2 [mm/min]	x_3 [mm]	x_4 [μV]	R_a [μm]
1500	228.6	25.4	883.3	1.3462
1500	228.6	76.2	1110.07	1.8796
1500	228.6	127.0	1056.26	1.778
1500	381.0	25.4	1463.67	2.794
1500	381.0	76.2	1255.47	2.1336
1500	381.0	127.0	1637.69	2.5146
1500	533.4	25.4	1472.73	3.0226
1500	533.4	76.2	1786.69	2.5908
1500	533.4	127.0	1980.14	2.8702
1250	228.6	25.4	1196.53	2.032
1250	228.6	76.2	1381.42	2.0828
1250	228.6	127.0	1201.78	2.3368
1250	381.0	25.4	1337.81	2.7178
1250	381.0	76.2	1521.43	2.4638
1250	381.0	127.0	1444.25	2.2098
1250	533.4	25.4	1300.14	3.2766

(*continued*)

Table A2. Continued.

x_1 [min^{-1}]	x_2 [mm/min]	x_3 [mm]	x_4 [μV]	R_a [μm]
1250	533.4	76.2	1725.29	2.4892
1250	533.4	127.0	1845.55	2.667
1000	228.6	25.4	911.13	2.3368
1000	228.6	76.2	1225.66	2.4384
1000	228.6	127.0	1425.78	2.5908
1000	381.0	25.4	1000.77	3.2766
1000	381.0	76.2	1486.15	2.7432
1000	381.0	127.0	1597.07	2.3368
1000	533.4	25.4	1033.83	3.7846
1000	533.4	76.2	1679.39	3.683
1000	533.4	127.0	1687.24	2.8448
750	228.6	25.4	930.96	2.7686
750	228.6	76.2	1254.68	2.5146
750	228.6	127.0	1171.25	2.413
750	381.0	25.4	950.24	3.175
750	381.0	76.2	1513.81	3.0988
750	381.0	127.0	1529.82	2.6416
750	533.4	25.4	1135.16	4.5212
750	533.4	76.2	1624.06	4.1402
750	533.4	127.0	1658.57	3.81

Depth of cut (x_3) = Original depth of cut × 100.
Vibrations (x_4) = Original vibrations × 10,000.
[a]The data shown are a part of the original data presented in Ref.[1]

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