PREDICTION OF SURFACE ROUGHNESS IN END MILLING WITH GENE EXPRESSION PROGRAMMING

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Abstract
Surface roughness has a great influence on the functional properties of the product. Finding the rules that how process factors and environment factors affect the values of surface roughness will help to set the process parameters of the future and then improve production quality and efficiency. Since surface roughness is impacted by different machining parameters and the inherent uncertainties in the machining process, how to predict the surface roughness becomes a challengeable problem for the researchers and engineers. In this paper, a method based on gene expression programming (GEP) has been proposed to construct the prediction model of surface roughness. GEP combines the advantages of the genetic algorithm (GA) and genetic programming (GP). By considering GEP as a very successful technique for function mining and formula found, it should be suitable to solve the above problem. On the basis of defining a GEP environment for the problem and improving the method of creating constant, the explicit prediction model of surface roughness can been constructed. To verify the feasibility and performance of the proposed approach, experimental studies conducted to compare this approach with some previous works are presented. The experimental results show that the proposed approach has achieved satisfactory improvement and obtained good results for several widespread studied problems.

Keywords: Surface roughness; Prediction model; Gene Expression Programming

1. Introduction

End milling process is one of the most fundamental and commonly encountered material removal operations in manufacturing process[1]. The surface roughness is one of the important properties for evaluating the workpiece quality during the end milling process[2]. The surface roughness plays a great part in fatigue strength and corrosion resistance, surface friction, light reflection, ability of holding a lubricant, electrical and thermal contact resistance, appearance, cost, etc [3, 4].High quality of the surface after end milling makes further machining of the surface not necessary, which brings about decreased power consumption and environment load. However, optimization of surface roughness is consistently challenged by its uncertainty of prediction model as well as various influencing parameters, which can be divided into controlled and non-controlled parameters. Main parameters of the first type includes spindle speed, feed rate, and depth of cut. And vibrations, tool wear, machine motion errors, and material non-homogeneity of both the tool and work piece, chip formation belong to the non-controlled parameters. The non-controlled cutting parameters are hard to reach and their interactions cannot be exactly determined.

Surface roughness optimization is concerned with developing efficient prediction model to minimize order of deviation. Successful implementation of machining process optimization requires development of models for prediction of surface roughness. The existing various approaches for predicting surface roughness are based on experimental investigation[5], designed experiment[6], Artificial Neural Network (ANNs)[2, 7] and Neuro-Fuzzy Systems(NFS)[8, 9]. The first category includes approaches that examine the effects of various factors through the execution of experiments and the analysis of the results. Regression analysis is often used to build models based on the experimental data. This approach is mainly used in cases where there can be no analytical formulation among the various factors. The second category includes the approaches based on Response Surface Method (RSM) and Taguchi's Design of Experiments (DoE). ANNs and NFS are recent developed Artificial Intelligence (AI) methods to predict surface roughness. The main advantages of the ANNs and NFS include the capability of approximating almost any function without requiring the knowledge of the process and the ability to handle noisy data. Recently, AI-based models have emerged as a preferred trend and are adopted by most researchers to develop models for near optimal conditions in machining, because of its fault-tolerant, approximated, uncertain and meta-heuristic. Although the ANNs and NFS can achieve a high accuracy in the prediction of surface roughness, their performance is limited by implicit models and unknown inner laws. Construct of explicit prediction model which can obviously reveal the inherent law of machining process would definitely contribute to the high quality of surface roughness. This paper proposes a novel method to accomplish this goal. The method used here to construct the prediction model is Gene Expression Programming (GEP).

GEP, invented by Ferreira[10], is a genotype/phenotype genetic algorithm that evolves computer programs of different sizes and shapes encoded in linear chromosomes of fixed length. The chromosomes are composed of multiple genes, each gene encoding a smaller subprogram. Furthermore, the structural and functional organization of the linear chromosomes allows the unconstrained operation of important genetic operators such as selection, mutation, transposition, and recombination. Thus, GEP is an artificial life system, well established beyond the replicator threshold, capable of adaptation and evolution. GEP surpasses the old GP system in 100–10,000 times[10, 11]. GEP has been successfully used in abrasive waterjet, but not in milling yet.

The new concept behind the linear chromosomes and the Expression Trees enables GEP to considerably outperform existing adaptive algorithms. Therefore, GEP offers new possibilities for solving more complex technological and scientific problems. Also important and original is the multi-genic organization of GEP chromosomes, which makes GEP a truly hierarchical discovery technique. And finally, gene expression algorithms represent nature more faithfully, and therefore can be used as computer models of natural evolutionary processes. According to its outstanding performance in function finding and formula mining, GEP used in this paper is to find the relationship between the process parameters and surface roughness which can help to predict the surface roughness explicitly.

The reminder of this paper is organized as follows: the approach based on GEP for prediction is introduced in Section 2. The proposed novel model and the predicting results for surface roughness prediction are explained in Section 3. In Section 4 a general conclusion is drawn.

2. GEP for prediction of surface roughness

For the modeling algorithms, GEP with three factors is used. The parameters used in the GEP models are given in Tables 1. The spindle speed (*Sp*), feed rate (*Fe*) and depth of cut (*Dep*) are assigned to the columns as independent input variables while arithmetic mean of *Ra* are used as dependent output variable. Therefore, a mathematical model of output variable is developed by using GEP.

Table 1 Parameters of the GEP models

Function set	+, −, ×, /	Mutation rate	0.2
Number of genes	20	IS transposition rate	0.4
Head size	30	RIS transposition rate	0.4
Linking function	+	Gene transposition rate	0.2
Number of generation	1000	One-point recombination rate	0.7
Number of population	100	Two-point recombination rate	0.8
Number of best individuals cloning	10	Gene recombination rate	0.5

The GEP based approach for prediction of surface roughness in end mill process includes the following major steps.

Step 1: Parameter setting. Set the parameters of GEP as Table 1.

Step 2: Initialization. Generate an initial population of random compositions of the functions and terminals of the problem.

Step 3: Assign each individual a fitness value according to how well it solves the problem. An average deviation of all sample data for individual Δ was introduced as fitness measure. It is defined as:

$$\Delta = \sqrt{\sum_{i=1}^{n} (G_i - E_i)^2 / n} \quad (1)$$

where n is the size of sample data and E_i and G_i are the actual R_a measured by an experiment and the predicted Ra calculated by a model, respectively.

Step 4: Create a new population of individuals.

(a) Selection operation. Individuals were selected according to fitness by roulette wheel coupled with the cloning of the best individual.

(b) Mutation operation. Mutation is the act of changing values of elements with certain probability P_m. In mutation operation each element of each gene in a chromosome is subjected to conversion from its current value to a new different feasible value.

(c) Transposition operations. Transposition refers to transposing part of the current chromosome to another position in the current chromosome. Insert sequence transposition (IS transposition), root transposition (RIS transposition) and gene transposition are all used in this method. In IS transposition, a sequence is randomly selected in the genome, and a copy of the transposition is made and inserted at any position in the head of a gene except at the start position. Differ from IS, RIS transposition is made and inserted at any position in the head of a gene except at the start position. In gene transposition an entire gene functions as a transposition and transposes itself to the beginning of the chromosome.

(d) Recombination operations. Different from transposition operations that aim at introducing diversity to the current single chromosome, recombination involves two or more chromosomes. One-point recombination, two-point recombination and gene recombination are used here. During one-point recombination, the chromosomes cross over a randomly chosen point to form two daughter chromosomes. In two-point recombination the chromosomes are paired and the two points of recombination are randomly chosen. In gene recombination an entire gene is exchanged during crossover.

Step 5: Compare the fitness and check if the specified stopping condition has been met.

Step 6: Display the optimal chromosome and the optimal fitness value.

3. Experimental Results

The experimental training data set and testing data set, which were also used in Lo[1], Ho et al. [9] and Dong[8], come from the work from Lou and Chen[12]. Lou and Chen used a high-speed steel (HSS) four-flute end milling cutter with a diameter of 3/4” in the experiment to machine 6061 aluminum alloy. Three factors, spindle speed (*Sp*), feed rate (*Fe*) and depth of cut (*Dep*), are used to analyze the influence on surface roughness (*Ra*). For directly comparing the GEP based approach with the ANFIS measure reported in Lo[1] and HTGLA-based method given in Ho et al. [9]and ANFIS with leave-one-out cross-validation approach in Dong[8], the same data set are selected in this work. The input variables of GEP are *Sp*, *Fe*, *Dep*, and the surface roughness is the output of GEP. The program was coded in C++ and implemented on a personal computer with a 2.0GHz Intel Core 2 Duo CPU.

The plan of tests is developed with the aim of relating the effects of the *Sp*, *Fe* and *Dep* with the surface roughness (*Ra*). The statistical treatment of the data is made in the following steps. The first step is to obtain a mathematical model for *Ra*, using GEP based on experimental results. Afterwards, the values calculated using the equation generated for the surface roughness models are compared with the experimental measurements. Lastly, a correlation graph is performed to do a comparison between the foreseen values from the model developed with the values obtained experimentally.

The obtained formulation corresponds to the following equation:

$$
\begin{aligned}
Ra &= 111.72219 + \frac{Fe - 7.13018}{(Sp + Sp \times Dep - 3 \times Dep) \times Dep + (2.68327/Fe) - Dep} \times Fe \\
&+ \frac{(51.33685 \times Dep \times (Dep + 2 \times Fe + 2.68327) + Sp + 14.26036) \times (Dep - 2.68327)}{57.96965} \\
&- \frac{Sp}{(7.13018 \times Dep - Sp + 2.68327) \times (2.68327 - Fe) - Fe} + \frac{Dep}{7.13018} + \frac{8.13018}{Sp + Dep} \\
&+ \frac{8.13018}{(Fe + Dep) \times Dep - Dep - Fe - 8.13018} + \frac{7.13018}{Sp \times Dep} - \frac{21.81547}{Sp} + 3Fe + \frac{Fe}{Sp} \\
&+ (21.60411 \times Fe/Dep + Fe - 8.13018) \times \frac{Dep}{Sp} - 4Dep \\
&+ \frac{(7.13018/Sp + 8.13018) \times 2.68327}{2.68327 - Fe}
\end{aligned} \tag{2}
$$

Where, *Sp*, spindle speed; *Fe*, feed rate; *Dep*, depth of cut; *Ra*, surface roughness.

The GEP model are utilized to predict the surface roughness of 24 testing data set listed in Lo[1], the predictive results are given in Table 2 together with predictive results using other methods. As is shown in Table 2, the predicted surface roughness by GEP agrees well with the experimental values.

Table 2. Comparison of predictive results(ANFIS: adaptive network-based fuzzy inference system; GLA: genetic learning algorithm; GP: Grid Partition method).

Test No.	E_i	GEP		ANFIS-GLA[9]		ANFIS-Triangular membership function [1]		ANFIS-Trapezoidal membership function [1]		ANFIS-GP	
		Predict	Error (%)	Predict	Error (%)	Predict	Error (%)	Predict	Error (%)	Predict	Error (%)
1	109	108.88	0.11	100.40	7.89	105.30	3.39	111.50	2.29	121.30	11.28
2	95	102.68	8.09	81.10	14.74	93.10	2.00	129.50	36.32	93.20	1.89
3	122	122.04	0.03	128.40	5.25	129.20	5.90	143.30	17.46	118.90	2.54
4	104	118.48	13.92	104.50	0.48	99.00	4.81	113.50	9.13	97.20	6.54
5	178	174.83	1.78	183.80	3.26	188.50	5.90	196.20	10.22	188.30	5.79
6	163	146.93	9.86	157.40	3.44	159.10	2.39	163.90	0.55	161.50	0.92
7	150	139.77	6.82	142.20	5.20	143.90	4.07	147.40	1.73	148.30	1.13
8	92	96.53	4.93	91.30	0.76	106.00	15.22	100.80	9.57	116.30	26.41
9	108	109.15	1.07	105.40	2.41	104.00	3.70	120.40	11.48	98.60	8.70
10	149	153.56	3.06	153.60	3.09	147.80	0.81	157.70	5.84	149.90	0.60
11	145	132.13	8.87	130.70	9.86	135.80	6.34	143.10	1.31	141.30	2.55
12	112	126.37	12.83	116.70	4.20	110.90	0.98	114.10	1.88	113.20	1.07
13	106	104.62	1.30	108.90	2.74	101.80	3.96	108.60	2.45	101.10	4.62
14	96	96.84	0.87	89.40	6.88	80.40	16.25	88.40	7.92	94.00	2.08
15	125	136.14	8.92	134.30	7.44	131.30	5.04	134.50	7.60	135.80	8.64
16	100	118.68	18.68	100.00	0.00	98.10	1.90	100.80	0.80	99.30	0.70
17	105	113.79	8.37	103.90	1.05	104.70	0.29	107.20	2.10	108.60	3.43
18	73	81.41	11.52	73.00	0.00	66.90	8.36	61.50	15.75	77.20	5.75
19	106	91.43	13.74	106.60	0.57	109.20	3.02	112.10	5.75	102.20	3.58
20	83	84.82	2.19	87.70	5.66	82.20	0.96	89.10	7.35	83.00	0.00
21	99	82.60	16.56	98.50	0.51	101.50	2.53	102.70	3.74	97.90	1.11

22	118	120.68	2.27	117.40	0.51	119.40	1.19	122.00	3.39	121.30	2.80
23	102	105.89	3.81	95.90	5.98	94.70	7.16	95.90	5.98	95.00	6.86
24	113	101.61	10.08	105.80	6.37	106.80	5.49	107.60	4.78	107.30	5.04

Figure1 shows the test evaluation of the GEP method for the Ra. It can be observed that there is a good agreement between the predicted and experimental surface roughness within a reasonable well correlation coefficient for *Ra*.

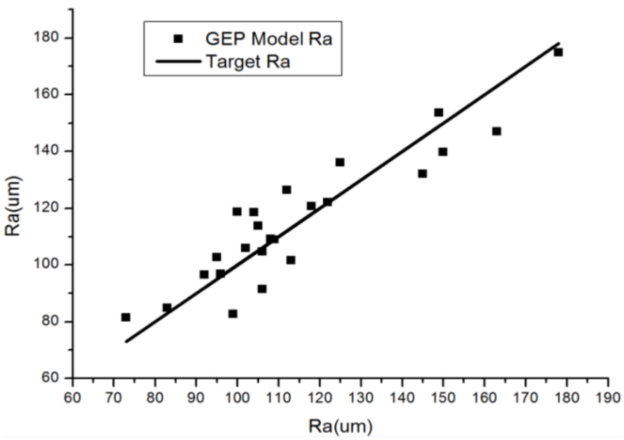

Fig.1. Test evaluation for *Ra* prediction.

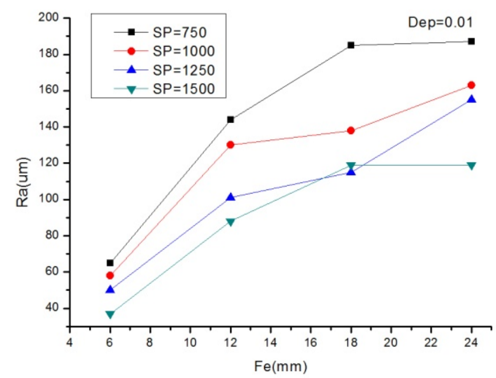

Fig.2. The effects of *Sp*, *Fe* and *Dep* on *Ra***(***Dep*=0.01**)**

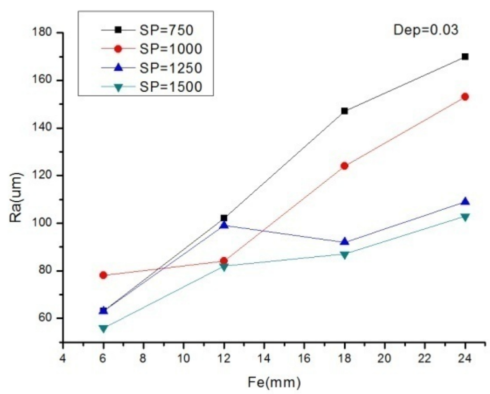

Fig.3. The effects of *Sp*, *Fe* and *Dep* on *Ra***(***Dep*=0.03**)**

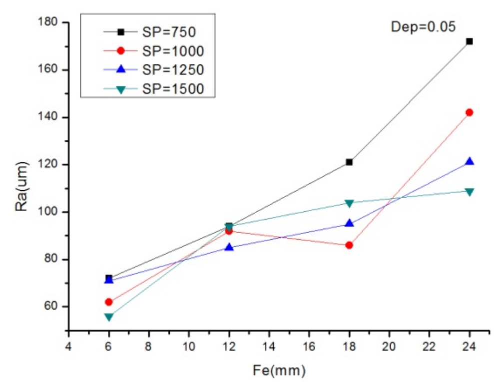

Fig.4. The effects of *Sp*, *Fe* and *Dep* on *Ra***(***Dep*=0.05**)**

Figure 2-4 shows the effect of depth of cut on the surface roughness with respect to the weight fraction and size of particles based on the GEP results. From this figure, it can observed that the depth of cut had a considerable effect on the surface roughness which increased with increasing the depth of cut. The most remarkable result is that the surface quality deteriorates as the depth of cut gets deeper.

Surface roughness gradually reaches its maximum value when the *Fe* reached to the maximum feed rate of the machine as shown in Figure 2-4. The values of *Ra* increase evidently along with the reduction of *Sp*, especially when the values of *Fe* are very large. The final membership functions of parameter *Dep* there is no obvious change after training. The above analysis indicates that among *Fe*, *Sp*, *Dep*, *Fe* and *Sp* has significant impact on surface roughness, while *Dep* has less significant impact. Furthermore, the values of *Ra* has positive correlation with the values of *Fe* and is anti-related with the values of *Sp*.

4. Conclusions and future researches

A mathematical model between the parameters of *Fe*, *Sp* and *Dep* is generated by GEP for the purpose of predicting surface roughness (*Ra*). And there is a good agreement between the predicted and experimental surface roughness. The main contributions of this paper include:

1. The results show that the GEP is an effective method for the surface roughness prediction.
2. This is the first time the GEP has been successfully used in predicting surface roughness in end milling, and the approach can be extended to other processing patterns.
3. An explicit model for the prediction of surface roughness has been constructed. Through analyzing the formula in the model, the inner laws of how the factors affect the values of surface roughness can be found. This work can be done later.

However, the predicting accuracy still needs to be enhanced. Future works can be done as follows: normalizing the data; finding effective method to generate constants; retaining good gene fragments during the evolution of the population.

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