Journal of Manufacturing Engineering, 2008, Vol.3, Issue.3

EMPIRICAL MODELING FOR SURFACE ROUGHNESS OF TURNING USING A RECENTLY EMERGED EVOLUTIONARY APPROACH

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ABSTRACT

Prediction of surface roughness is essential in any machining process as it plays a vital role in determining the quality of components. A good quality surface improves fatigue strength, wear resistance, and corrosion resistance. The present work involves the development of a mathematical model for surface roughness of a turning process based on a recently emerged evolutionary approach called Genetic programming (GP). The machining parameters of turning such as cutting speed, feed rate, and nose radius are considered as the input variables. Two sets of experimental data were taken: training data set and testing data set. The model established by GP based on the training data set is validated with the testing data set.

Keywords: Surface roughness, turning, genetic programming, and evolutionary process

1. Introduction

Surface roughness plays an important role in any machining process to determine the quality of machined components. It not only affects the operational characteristics but also the manufacturing cost. The properties of machined components such as fatigue strength, wear resistance, and corrosion resistance are greatly affected by the surface roughness. Surface roughness refers to the magnitude of irregularities of material resulted during machining operation. There are several ways to describe surface roughness. One of them is average roughness, which is quoted as R_a. R_a is the most commonly used and internationally recognized parameter for measuring surface roughness. Theoretically, R_a represents the arithmetic average value of departure of the profile from the mean line throughout the sampling length [1].

Surface roughness is influenced by several factors such as tool geometry, cutting parameters, tool wear, tool deflection, chatter, cutting fluid and work piece properties. Out of the above-mentioned factors, cutting parameters are the most significant factors that affect the surface roughness. Therefore in the present work, the mathematical model in terms of cutting conditions is developed. However, determination of surface roughness based on theoretical analysis is very difficult as it is dynamic, complicated and completely process dependent. Therefore several attempts have been made in the literature to develop the empirical models for surface roughness. Most approaches involve the usage of Response surface methodology [2,3,4] but in the Response surface methodology (RSM), a model of certain degree has to be determined in advance. Because of this pre-specified degree of the model, RSM may often not handle a highly non-linear responsive data as exist in machining processes. Some other approaches were based on using Neural networks for the prediction of surface roughness [5]. However, Neural networks do not establish the quantitative relationships between the input variables and the output parameters. In the present work, an efficient evolutionary approach called Genetic programming (GP) is proposed for the quantitative modeling of surface roughness based on experimental values and the proposed approach can handle any amount of complexity between input variables and output parameters.

2.Proposed Method – Genetic Programming

Evolutionary approaches attempt to find the best solution to a problem by mimicking the process

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of evolution in nature using Darwin's theory of *survival of the fittest*. Individual potential solutions are selected based on their fitness from the initially generated random population. The potential solutions are then recombined to produce better solutions. The extreme popularity of these techniques is due to their success at searching highly complex non-linear spaces and their robustness in practical applications.

Genetic programming is a relatively new approach when compared to other variations of evolutionary algorithms such as evolutionary strategies, genetic algorithms and evolutionary programs. The main principles of Genetic programming (GP) and its related terminology were developed by Koza [6]. Unlike the other evolutionary algorithms, which are used for optimization, GP is used for empirical modeling of complex systems.

GP evolves solutions in the form of computer programs of uneven length. In GP, a solution to a problem is represented as a computer program, which has a hierarchical composition of primitive *functions* and *terminals* appropriate to particular problem domain. In GP terminology, inputs are usually called *terminals* and user specifies a number of *functions* that manipulate terminals. The set of primitive *functions* typically include: arithmetic operations (+, -, *, /), boolean operations (AND, OR, NOT), logical operations - (IF-THEN-ELSE), and non-linear functions (sin, cos, tan, exp, log). Typical representation of an individual in GP for the expression {(2+x)(z)}-3xz is shown in Fig 1**.** The set of functions in the representation are {constant, -, *, +} and the set of terminals are {x, y, z}.

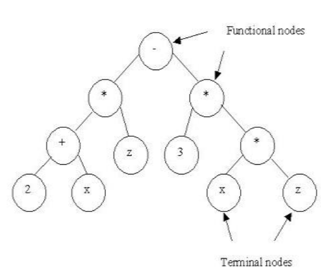

Fig 1. Representation of GP tree

2.1 Generation of Initial Population

GP starts with generation of an initial population by random compositions of the functions and terminals. The initial population is generated in such a way that it has a good diversity of individuals of different shapes and sizes. One of the most commonly used methods for ensuring the diversity is by the ramped half-and-half algorithm [6]. This method creates an equal number of trees for each depth between 2 and maximum depth specified by the user.

2.2 Genetic Operators

The fitter initial population is gradually improved through the genetic operators: *reproduction*, *crossover*, and *mutation*. Reproduction is the exploitation phase of search in which emphasis is given to the high fit individuals. The reproduction operation ensures that good individuals remain in the population. It selects an individual from the current generation and copies it, without alteration, into the next population. There are a number of reproduction operators in the literature for propagating the influence of the best-fit individuals of current generation to the next generation; most commonly used are tournament selection, rank selection and roulette wheel selection. A new mating pool is found after the reproduction operator whose size is same as the parent population and individuals have representation in the new population proportional to their fitness.

Exploration in GP is brought about by crossover and mutation operators. In crossover operation, two of the fittest individuals are randomly selected as the parent programs and selected parts of the parents are swapped to hopefully produce better programs. This process is illustrated in Fig. 2. It could be noted that highlighted parts of the parent trees in the figure exchange each other to produce two offspring. The expressions for the two parents and two offspring are also presented. To preserve good solutions obtained so far, not all individuals are subjected to crossover. Although mutation maintains diversity but it is mainly intended to prevent getting stuck on a local minimum. Usually, one randomly selected node is replaced with another one from the same set except itself. The process of mutation is illustrated in Fig. 3.

2.3 Termination Criterion

Implementation of above three operators constitutes one generation and the procedure is repeated until a termination criterion is met. The termination criterion can be either a prescribed number of generations or sufficient quality of the solution. The number of generations required for a satisfactory solution depends on the complexity of the problem.

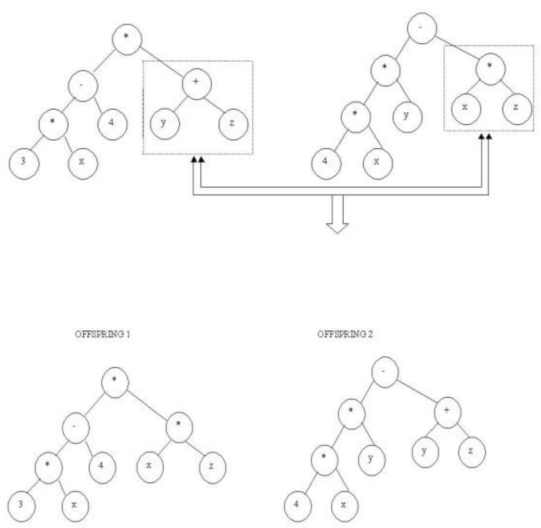

Fig .2 Illustration of Crossover operator

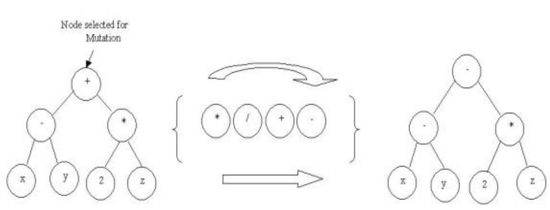

Fig 3. Illustration of Mutation operator

3. Experimental Details

Experiments were conducted using Hardinge CNC Turning center on 6081 Aluminum. To perform turning, cemented carbide inserts of different nose radius were used. Cutting speed (x_1), feed rate (x_2), and nose radius (x_3) were considered as the input variables as they significantly affect the surface roughness. A constant depth of cut of 0.25mm is maintained for all experiments. Based on the feasible values of machine tool and cutting tool , five levels of cutting speed (1500,1800,2100,2400,2700rpm), 8 levels of feed (0.05,0.1,0.15,0.2,0.25,0.35,0.45), and 4 levels of nose radii (0.2,0.4,0.55,0.8mm) are taken. The surface roughness R_a was measured using a portable Mitutoyo Surftest instrument with a traverse length of 8mm. Each measurement is repeated four times, and the average value is considered to establish the model. The experimental values were divided into two sets: training data set and testing data set and are listed in Tables 1 and 2 respectively.

Table 1. Training data set

x_1(rpm)	x_2(mm/rev)	x_3(mm)	R_a
1500	0.05	0.2	0.78
1500	0.15	0.2	3.88
1500	0.25	0.2	4.84
1500	0.2	0.2	4.1
1800	0.15	0.2	2.82
1800	0.25	0.2	4.87
1800	0.1	0.2	1.78
1800	0.2	0.2	4.34
2100	0.05	0.2	0.82
2100	0.15	0.2	3.86
2100	0.25	0.2	4.86
2100	0.2	0.2	4.4
2400	0.05	0.2	0.94
2400	0.25	0.2	4.88
2400	0.1	0.2	1.76
2400	0.2	0.2	4.56
2700	0.05	0.2	0.94
2700	0.15	0.2	2.94
2700	0.25	0.2	4.89
2700	0.1	0.2	2.1
1500	0.05	0.4	0.42
1500	0.15	0.4	1.2
1500	0.35	0.4	2.76
1500	0.45	0.4	3.6
1800	0.15	0.4	1.2

1800	0.25	0.4	2.1
1800	0.35	0.4	3.3
1800	0.45	0.4	3.6
2100	0.05	0.4	0.48
2100	0.25	0.4	2.22
2100	0.35	0.4	3.1
2100	0.45	0.4	3.98
2400	0.05	0.4	0.42
2400	0.15	0.4	1.2
2400	0.35	0.4	2.76
2400	0.45	0.4	3.88
2700	0.15	0.4	1.2
2700	0.25	0.4	2.31
2700	0.35	0.4	3.22
2700	0.45	0.4	4.79
1500	0.05	0.55	0.42
1500	0.25	0.55	1.9
1500	0.35	0.55	2.52
1500	0.45	0.55	4.78
1800	0.05	0.55	0.42
1800	0.15	0.55	1.54
1800	0.35	0.55	2.38
1800	0.45	0.55	4.66
2100	0.15	0.55	1.54
2100	0.25	0.55	2.1
2100	0.35	0.55	2.3
2100	0.45	0.55	3.68
2400	0.05	0.55	0.41
2400	0.25	0.55	1.98
2400	0.35	0.55	2.7
2400	0.45	0.55	4.18
2700	0.05	0.55	0.38
2700	0.15	0.55	1.48
2700	0.35	0.55	2.89
2700	0.45	0.55	3.78
1500	0.15	0.8	1.41
1500	0.25	0.8	2.64
1500	0.35	0.8	4.22
1500	0.45	0.8	4.46
1800	0.05	0.8	0.67
1800	0.25	0.8	2.5
1800	0.35	0.8	3.76
1800	0.45	0.8	4.76
2100	0.05	0.8	0.48
2100	0.15	0.8	1.41
2100	0.35	0.8	3.86
2100	0.45	0.8	4.68
2400	0.15	0.8	1.38
2400	0.25	0.8	2.4
2400	0.35	0.8	3.54
2400	0.45	0.8	4.81
2700	0.05	0.8	0.41
2700	0.25	0.8	2.64
2700	0.35	0.8	3.36
2700	0.45	0.8	4.8

Table. 2: Testing data set

x_1(rpm)	x_2(mm/rev)	x_3(mm)	R_a
1500	0.1	0.2	1.84
1800	0.05	0.2	0.92
2100	0.1	0.2	1.89
2400	0.15	0.2	3.21
2700	0.2	0.2	4.2
1500	0.25	0.4	1.98
1800	0.05	0.4	0.42
2100	0.15	0.4	1.24
2400	0.25	0.4	2.34
2700	0.05	0.4	0.43
1500	0.15	0.55	1.2
1800	0.25	0.55	1.89
2100	0.05	0.55	0.41
2400	0.15	0.55	1.24
2700	0.25	0.55	1.8
1500	0.05	0.8	0.48
1800	0.15	0.8	1.38
2100	0.25	0.8	2.8
2400	0.05	0.8	0.43
2700	0.15	0.8	1.34

4. Implementation

To decide the elements of functional sets, initially some trial runs were conducted with different combinations. It was found that the probability of successful solution is the greatest, when only the basic arithmetic functions were used. The arithmetic elements that were considered are addition, subtraction, multiplication, and division. The terminal set consists of all input variables of the welding process that have been taken into consideration in the present study. In order to increase the diversity of the individuals, the random floating-point numbers from the range, (-20, 20), were added to the set of the terminals. An average percentage deviation of all experimental data for an individual was introduced as the fitness measure and is defined below:

$$\delta = \sum_{i=1}^{n} \frac{\delta_i}{n} \quad (1)$$

where, δ is the fitness, n is the total number of observations and δ_i is the percentage deviation of single sample data. The percentage deviation of single sample data produced by an individual is

$$\delta_i = \frac{|M_i - P_i|}{M_i} \times 100\% \quad (2)$$

where, M_i is the experimentally measured value and P_i is the value predicted by the model. It is assumed that the model generated is a successful solution, if its average percentage deviation of the experimental data is less than 10%. Preliminary experiments were performed to determine the best parameter settings for the GP. These preliminary test runs in the GP system were executed for the output parameters independently. Based on these experiments, the parameter values shown in Table 3 were finally selected to generate the models. Evolutionary algorithms are generally robust to variations of control parameters [7]. However, some guidelines are provided in ref [8] for choosing the control parameters of standard GP. The software is developed in VC++ on a Pentium system with 2.8GHz processor.

Table 3. Control parameters

Population size	300
Number of generations	125
Number of runs	10
Crossover probability (%)	85
Mutation probability (%)	5
Reproduction probability (%)	10
Selection method	Tournament

Tests with populations of different sizes of 200, 300 and 500 were also performed. In all cases, the best results were achieved with the large populations. However, the computation times were also increased from an average of 3 minutes for the population size of 100 to more than 10 minutes for the population size of 500. Thus, a reasonable size of 300 was considered. In case of oversized programs, to avoid the excessive amount of computer time, the depth of initial generated programs was limited to 6 and the depth of the program created by crossover was limited to 20. If an offspring had a depth of more than 20, it was replaced by one of its parents. The generated model by the proposed algorithm for the roughness is given in equation (3).

Figs. 4 and 5 exhibit the percentage deviations of the best model generated by the algorithm for the training and the validation data sets respectively. It can be observed from the Fig.4 that the most deviations of the individuals are less than 15%. The deviations of the individuals of the testing data set are well below 10%.

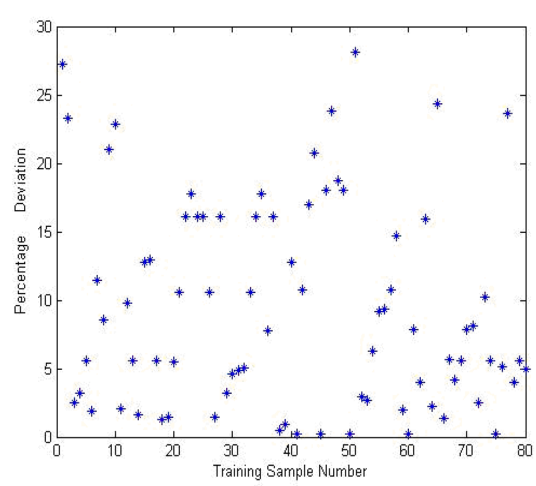

Fig.4 Percentage deviation for Training data set

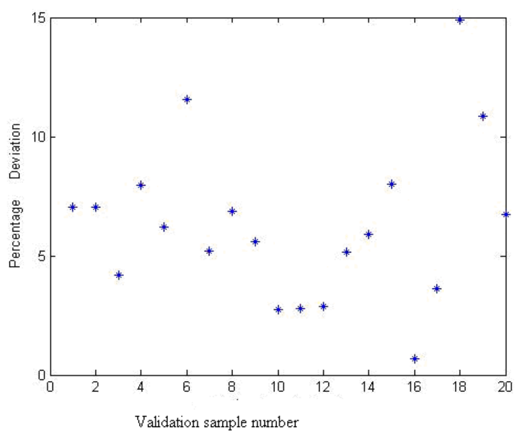

Fig.5 Percentage deviation for Validation data set

$$R_a = \left[\left(\frac{0.592x_2^2}{\left(x_3^2 - 0.179x_3\right)}\right) + 4.924x_2\right] - \left[\frac{1.949x_3}{\left[\left[13 - \left(\frac{7.702x_2}{0.703 + x_3}\right)\right] + 0.593x_2 - \left(\frac{11.703x_2 + 11.073}{x_2 + x_3}\right) + 6x_2x_3 - x_3\right]}\right]$$

5. Conclusions

Surface roughness is an important measure of the technological quality of machined component product. It also greatly influences manufacturing cost and determines machine tool productivity. Being such an important measure, the present work proposes an evolutionary approach for empirical modeling of surface roughness of turning operation using Genetic programming (GP). The proposed approach neither requires any strict mathematical rule nor any prior knowledge of how to get the solution of the problem. GP uses evolutionary principles to evolve automatically mathematical models that best suit to the given experimental data. No assumptions about the shape, size, and complexity of the problem are required. GP is such a generalized approach that this can be applied any machining process under any number of input variables.

6. References

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