International Journal of Engineering Research
Volume No.5 Issue: Special 2, pp: 407-409

ISSN:2319-6890)(online),2347-5013(print)
11-12 Feb. 2016

Development of an Empirical Model for Surface Roughness in a Non-Conventional Drilling Process - 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. The present work involves the development of an empirical model for surface roughness of a non-traditional hole-making method, friction drilling process based on a recently emerged evolutionary approach called Genetic programming (GP). The parameters such as drilling speed, feed rate, and tool angle are considered as the input variables. Based on two separate datasets the accurate model was established by GP.

Keywords: Surface roughness, drilling, genetic programming, evolutionary approach

I. 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. 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 [1] 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 [2]. 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 modelling of surface roughness based on experimental values and the proposed approach can handle any amount of complexity between input variables and output parameters.

II. Proposed method-Genetic Programming

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 [3].

Unlike many other evolutionary algorithms, which evolve fixed length strings of binary integers or real numbers, 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 (y-z)(x+z) is shown in Fig 1**.** The set of functions in the representation are {-, *, +} and the set of terminals are {x, y, z}.

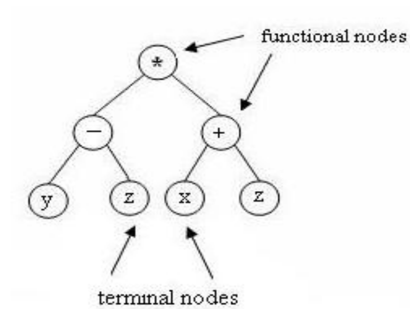

Fig.1.Representation of GP tree

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 [3]. This method creates an equal number of trees for each depth between 2 and maximum depth specified by the user.

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

ISSN:2319-6890)(online),2347-5013(print)
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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 [5].

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. Mutation maintains diversity and prevents getting struck 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.

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 [5]. The number of generations required for a satisfactory solution depends on the complexity of the problem.

III Experimental Details

The experiments were carried on 5 axes CNC vertical machining center having speed range of 60RPM to 9000 RPM. The materials selected for this study is Aluminium hollow channel as work piece material and HSS as tool material. Work piece dimensions are: 50mm Length x 25mm Breadth x 2 mm thickness and has been selected to drill the holes. Three (3) Friction drilling tools diameter with 8mm made of HSS have been selected for experimental trails. The selected spindle speeds were 2000rpm, 2500rpm, 3000rpm, feed rates were 30mm/min, 45mm/min, 60mm/min. Tool material was HSS which has 35°,45°,55^{o} conical angle and 12.50mm cylindrical region length.. The experimental values were divided into two sets: training data set and testing data set respectively. The process parameters and their levels are shown in table 1.

S.No	**Process Parameters**	**Levels**		
		1	2	3
1	Speed(RPM)	2000	2500	3000
2	Feed(mm/min)	30	45	60
3	Conical angle	35°	45°	55°

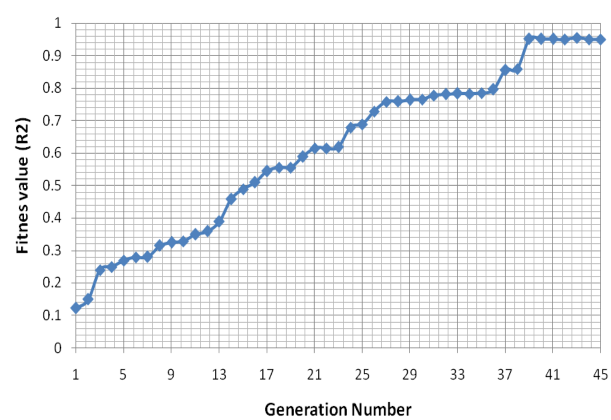
III. Implementation & Results

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 drilling 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 the correlation coefficient R^2 of all experimental data for an individual was introduced as the fitness measure and GP was continued until a value as close as possible to the maximum value of R^2 was obtained [6]. R^2 was used as the fitness measure in order to check whether the fitted models actually describe the experimental data. Preliminary trials 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 trials, the parameter values shown in Table 2 were finally selected to generate the models. Evolutionary algorithms are generally robust to variations of control parameters [4]. However, some guidelines are provided in ref [7] for choosing the control parameters of standard GP. The commercial code GP Studio software was used to generate the models trees.

Table 2. Control parameters

Population size	800
Number of generations	45
Number of runs	8
Crossover probability (%)	85
Mutation probability (%)	5
Reproduction probability (%)	10
Selection method	Tournament

$$R_a = 0.1854x_3 - \frac{90}{\left(-0.234 - 0.0105x_1 + \frac{0.236}{x_2} + \frac{x_2x_3^2}{x_1x_2 + 2x_3^2 - x_2 + 127.25x_3}\right)}$$



doi : 10.17950/ijer/v5i2/024

Tests with populations of different sizes of 300, 500 and 1000 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 1000. Thus, a reasonable size of 800 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. After the implementation of the algorithm, the following model was generated.

IV. Conclusion

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 a new and efficient approach for empirical modeling of surface roughness 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.

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