Genetic Evolutionary Approach for Cutting Forces Prediction in Hard Milling

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Z. Naturforsch. **66a**, 675–680 (2011) / DOI: 10.5560/ZNA.2011-0026 Received January 10, 2011 / revised May 30, 2011

Hard milling is a very common used machining procedure in the last years. Therefore the prediction of cutting forces is important. The paper deals with this prediction using genetic evolutionary programming (GEP) approach to set mathematical expression for out cutting forces. In this study, face milling was performed using DIN1.2842 (90MnCrV8) cold work tool steel, with a hardness of 61 HRC. Experimental parameters were selected using stability measurements and simulations. In the hard milling experiments, cutting force data in a total of three axes were collected. Feed direction (F_x) and tangential direction (F_y) cutting forces generated using genetic evolutionary programming were modelled. Cutting speed and feed rate values were treated as inputs in the models, and average cutting force values as output. Mathematical expressions were created to predict average F_x and F_y forces that can be generated in hard material milling.

Key words: Cutting Forces; Hard Material Milling; Genetic Evolutionary Programming.

1. Introduction

Milling is a very commonly used manufacturing process in industry due to its versatility to generate complex shapes in variety of materials at high quality. Due to the advances in machine tool, computer numerical control (CNC), computer aided design/computer aided manufacturing (CAD/CAM), cutting tool, and high speed machining technologies in the last couple of decades, the volume and importance of milling have increased in key industries such as aerospace, die and mold, automotive and component manufacturing [1]. With the advances in cutting tool technologies, hard milling has been recently employed to machine hardened steels (> 30 HRC) in making dies and molds for various automotive and electronic components as well as plastic molding parts [2]. Previous research in hard milling has focused on tool life [3], surface smoothness [4], white layer effect [5], cutting force modelling [6], machine stability [6], and optimum cutting parameters [7]. In milling, cutting forces are one of the basic parameters for selecting cutting parameters, and in many cases the most important [8]. The measurement of cutting forces is not always possible under experimental conditions; however, they are usually modelled using intelligent methods.

Modelling cutting forces is usually a difficult procedure because of the tool–workpiece geometry and the complexity of the cutting configuration. Analyzing the cutting force is difficult because many machine parameters are involved. As cutting forces affect many parameters (cutting speed, feed rate, depth of cut, tool holder geometry, tool corrosion, physical and chemical characteristics of machine parts, etc.), developing a proper model is very demanding [9].

Previous works on the subject include the study of Milfelner et al., who came up with the genetic equation of cutting forces in milling with spherical ended tools. They worked on a model that can predict the maximum cutting force using radial depth of cut, feed rate, and cutting speed values. Their model uses the functions of adding, subtracting, multiplying, and dividing. They have produced a genetic equation that can predict cutting forces with a 3.83% margin of error [9].

Kovacic et al. conducted a study on predicting cutting forces in milling using the evolutionary approach.

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They have processed two separate workpieces in an vertical machining center, and measured F_x , F_y , and F_z cutting force values with different parameters of workpiece yield stress and hardness value, tool diameter, depth of cut, spindle speed, feed rate, and process type. They have generated mathematical equations for all three cutting force axes using these parameters [8].

This study conducts experiments, using CBN 300 cutting inserts, on a cold work tool steel workpiece with a hardness of 61 HRC and DIN 1.2842 (90MnCrV8), and the cutting force value generated in the experiments were modelled using genetic evolutionary programming (GEP). After the modelling, a mathematical expression for average F_x and F_y forces that can be generated in hard material milling was produced.

2. Genetic Evolutionary Programming (GEP)

Genetic evolutionary programming (GEP) is, like genetic algorithms (GA) and genetic programming (GP), a genetic algorithm as it uses populations of individuals, selects them according to fitness, and introduces genetic variation using one or more genetic operators. The fundamental difference between the three algorithms resides in the nature of the individuals: in GA the individuals are linear strings of fixed length (chromosomes); in GP the individuals are nonlinear entities of different sizes and shapes (parse trees); and in GEP the individuals are encoded as linear strings of fixed length (the genome or chromosomes) which are afterwards expressed as nonlinear entities of different sizes and shapes [10].

The genetic evolutionary programming algorithm is composed of linear chromosomes stable in number and length which can be reproduced by the computer program. The chromosomes derived can be expressed in different shapes and dimensions in 'explanation trees' (ET) form using the operators of GEP.

The advantages of a system like GEP are clear from nature, but the most important should be emphasized. First, the chromosomes are simple entities: linear, compact, relatively small, easy to manipulate genetically (replicate, mutate, recombine, transpose, etc.). Second, the ET are exclusively the expression of their respective chromosomes; they are the entities upon which selection acts and, according to fitness, they are selected to reproduce with modification. During reproduction it is the chromosomes of the individ-



Fig. 1. Example of a mathematical explanation tree.

uals, not the ET, which are reproduced with modification and transmitted to the next generation [10].

In the GEP algorithm, all the problems, from the simplest to the most complicated, are expressed as ET. The ETs are composed of operators, functions, constants, and variables. For example in a chromosome list EP variables such as $\{+, -, *, /,$ sqrt, 1, *a*, *b*, *c*, *d*, sin, cos} are possible. Here, when a chromosome as sqrt. *. +. *. *a*. *. sqrt. *a*. *b*. *c*. /. 1. -. *c*. *d* is formed, in this chromosome full stop '.' represents 'sqrt' square root operation for dividing each gene and easy reading; '1' represents a constant; '+, -, *' represent algebraical statements and '*a*, *b*, *c*, *d*' represent the names given to the variables.

The relationship between the variables is stated as Karva notations by Candida Ferreire who developed the GEP algorithm. Karva notations are expressed with 'explanation tree' (ET). The explanation tree formed with Karva notation belonging to the evolutionary programming gene is demonstrated in Figure 1 [10].

The mathematical expression of the explanation tree in Figure 1 is as follows:

$$\sqrt{(a+b) \times (c-d)}.$$
(1)

3. Experimental Studies

Face milling experiments on cold work tool steel with a hardness level of 61 HRC were conducted in a Hardford VMC 1020 vertical machining center. Depth of cut, feed rate, and cutting speed values were selected using analytical stability curves generated by measuring machine-tool stability (Fig. 2) [11]. Axial depth of cut was kept constant at 0.6 mm. A total of 32 experiment parameters were generated by selecting eight separate spindle speeds (2650, 2280, 1760, 1405, 1170, 1005, 875, 780 r/min) and four separate



Fig. 2. Analytical stability lobes diagram of hard milling test [11].

feed rates (0.05, 0.075, 0.1, 0.15 mm/tooth). A surface cutter with a diameter of 63 mm was used in the experiments. CBN inserts were used as cutting tool in the experiments (Table 1) [12].

Workpiece material, steel 90MnCrV8 (AISI – O2, EU - 90MnCrV8) is a cold work tool steel, with high dimensional stability at heat treatment, very high resistance to cracking, high machinability, medium toughness and resistance to wear. Hardness after annealing is max 229 HB. After quenching, the possible to

Table 1.	Cutting	tool s	pecificat	tions	[12	21.

Tool specifications	CBN300		
ISO Code	SNEN0903ENE-M06		
Composition	Approximate CBN content90% Average particle size (µm)22 BinderAl ceramic FormatSolid		
Physical Characteristics	Knoops hardness GPa 30.4 Thermal conductivity [Wm ⁻¹ K ⁻¹] (20 °C)		
Tool geometry	Size 9.525 mm L 9.525 mm s 3.18 mm B 0.9 mm r_e 0.8 mm Rake angle 0°		

achieve hardness is 63–65 HRC. Field of application of 90MnCrV8 is in compress measuring tools, machine knives for the wood, paper, and metal industry, cold cutting shear blades, and thread cutting tools [13]. The chemical properties of workpiece material is as follows: 0.88% carbon, 0.29% silicon, 2.07% manganese, 0.26% chromium, 0.024% phosphorus, 0.009% sulfur, and 0.08% vanadium [14].

Cutting forces were measured for F_x , F_y , and F_z directions in each experiment using a Kistler dynamometer type 9257B. Based on the connection of the dynamometer to the vertical machining center table, the F_x force was in the feed direction. In cutting force measurements, the chip volume was fixed at 5896.8 mm³. Cutting signals were measured until the volume of cutting reached that point. Then, the arithmetic mean of the cutting force signals was calculated to generate average cutting force values. Figure 3 displays the change in average F_x and F_y forces by cutting speed and feed rate.

As we can see in Figure 3, when cutting speed is kept constant, both F_x and F_y cutting forces increase as feed rate increases. The smallest and the largest cutting force values were measured in the F_x direction. The smallest cutting force was measured as 397.95 N in the experiment, with a cutting speed of 451.3 m/min and a feed rate of 0.05 mm/tooth; the largest cutting



Fig. 3. Change in average cutting force by cutting speed and feed rate; (a) average F_x cutting force, (b) average F_y cutting force.

force was measured as 2396.26 N in the experiment, with a cutting speed of 524.5 m/min and a feed rate of 0.15 mm/tooth.

4. Modelling Cutting Forces Using Genetic Evolutionary Programming

In this study, three types of modelling techniques were used, but it was seen that neural networks and fuzzy logic are not successful at prediction of cutting forces. The most successful model of the modelling was obtained by GEP. Two separate models and mathematical expressions were developed for cutting force predictions, using the average F_x and F_y values measured in the experiments conducted with CBN 300 cutting inserts.

As the axial depth of cut was kept constant in the experiments conducted, cutting speed and feed rate values were used as inputs, and average cutting force values were used as outputs. In both models, 75% of the 32 experiment parameters were used for training and 25% for testing. Training and test values were shifted among themselves, and the data group with the highest modelling success was taken as the model.



Fig. 4. Genetic evolutionary programming model set up for CBN 300 F_x force prediction; (a) average F_x , (b) average F_y .



Fig. 5. Comparison of experimental values and values generated by evolutionary programming for cutting forces; (a) F_x cutting forces, (b) F_y cutting forces.

For the model that uses average F_x and F_y values, experimental data were trained in different chromosome and mutation values. As a result of training the number of chromosomes 50 and the number of mutations 0.04 were determined. For average F_x cutting forces, the truth value of $R^2 = 0.80$ was reached after 735 632 iterations, and for average F_y cutting forces, the truth value of $R^2 = 0.91$ was reached after 433 423 iterations (Fig. 4).

Success rates of the models set up for average F_x and F_y forces are values acquired from the models with the best fit, selected by varying training and test values, and trying various functions.

Functions used for average F_x forces were addition (+), subtraction (-), multiplication (*), division (/), square root (*Q*), exponential function (*E*), natural logarithmic function (*L*), 10^x (~), logarithmic function (*K*), cosine (*C*), and 1/x (*Y*). The visual basic code of the model with the 80% success rate is generated. The mathematical expression of the visual basic code generated by the program for the prediction of average F_x force value is as follows:

$$F_x = 10^{\exp\sqrt{\exp(V)}} + \frac{1}{\cos(V \cdot f_z)} + \frac{\log\left(10^{\log(V)}\right)}{\frac{\exp(f_z)}{f_z} \cdot \frac{1}{V}} + \cos\left(\left(\exp\left(f_z\right) \cdot (f_z + V)\right) \cdot V.\right)$$
(2)

Expressions in the equation are defined as follows:

 F_x = average F_x cutting force for CBN 300 cutting inserts, V = cutting speed (m/min), and f_z = feed rate (mm/tooth).

Functions used for average F_y forces were addition (+), subtraction (-), multiplication (*), division (/), Power (^) square root (*Q*), exponential function (*E*), natural logarithmic function (*L*), logarithmic function (*K*), tangent (*T*), floor (*F*), and 1/x (*Y*). The visual basic code of the model with the 91% success rate is generated. The mathematical expression of the visual basic code generated by the program for the prediction of average F_y force value is as follows:

$$F_{y} = ((\tan(\log(V))) + f_{z}) \cdot \frac{1}{f_{z} - \operatorname{int}(V)} + (V - (\tan(V^{f_{z}})))^{\sqrt{f_{z}}} - \log(V) + \frac{V}{\tan(\frac{1}{f_{z}})}$$
(3)
- $\tan(\log(V)) + V.$

In above equation, int(V) means integer(V). This expression is used to convert a decimal number to an integer.

Figure 5 displays the scatter diagram of the average F_x and F_y cutting force values measured in the experiments, and the average cutting force values predicted by the genetic evolutionary programming method.

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As we can see in Figure 5a, the relationship between experimental values and values calculated by evolutionary programming, according to the mean square error, is 0.82. In Figure 5b, the relationship between experimental values and values calculated by evolutionary programming, according to the mean square error, was found to be 0.92. These rates are an indicator of success for the models set up.

5. Results

Cutting force and modelling results acquired from the face milling of 90MnCrV8 cold work tool steel using CBN cutting inserts are as follows:

- When we examined cutting force signals, we observed that when the cutting speed is kept constant and the feed rate is increased, both *F_x* and *F_y* cutting force values have increased as well.
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- A nonlinear relationship was found between GEP on the one hand and cutting speed and feed rate on the other hand, and this relationship was expressed using mathematical equations.
- Observed F_x and F_y cutting force values were compared with values generated by the mathematical equations created based upon the GEP model. Success rates of the equations were found to be 82% for F_x force values, and 92% for F_y values, both rather high prediction figures.
- The genetic programming model can be integrated into intelligent production systems, and provide advantages in the machining sector by offering time and cost flexibility in process modelling and production.
- The genetic programming model can be extended by including other parameters (like tool geometry, machine-tool dynamics, axial and radial depth of cuts, etc.), and more sensitive cutting force models can be developed.
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