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ASPECTS REGARDING THE USE OF GENETIC PROGRAMMING IN MODELLING THE CUTTING PROCESS

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Abstract: *The paper deals with the milling force modelling concerning average and maximum forces. From the experience of the late decades, the modelling using numerical methods of approximation such as multiple regression algorithms has proved that the models are not enough accurate and the error could be significant. This research tries to replace the classical models using reliable ones, the milling process still remaining a challenge for researchers. The main purpose of the work is to obtain a function of three variables (cutting depth, feed per toot and cutting speed) using genetic algorithms. The achievement of the genetic relation is important in cutting force estimation and also in optimization of cutting parameters if the set of experiments are enough. The milling investigations were carried out on a CNC machining centre, FIRST MCV 300, with three axes. The measurements were made with a Kistler dynamometer fixed on the machine tool mass. The workpiece material used for the experimental tests was a 173 mm length, 85 mm width, and 35mm high piece of steel. The workpiece was initially tested in order to establish the material (spectrometric test and hardness measuring). The cutting tool used is CoroMill R 365-080Q27-S15M with cutting tool inserts R365-1505ZNE-PM 4230 (Sandvik Coromant). The experimental plan was chosen according to Taguchi's Method and consist of 16 tests based on three variables. The fit between data and the model is very good, very good result being achieved after maximum 1 000 generations.*

Key words: *milling, milling cutter, cutting parameters, experimental plan, cutting forces components, average cutting force, maximum cutting force, genetic algorithms, genetic model.*

1. INTRODUCTION

The genetic algorithms (GA's) are computerized models which compete with evolutionary biological models in order to solve optimizations or search problems [1]. They began to be recognized as optimization techniques with the works of J. Holland in 1975. Genetic algorithms have been used as efficient optimizing solutions when the analytical modelling becomes complex and the differential equations cannot be solved. The genetic algorithms rely on the concept „survival of the fittest". The initial solutions of genetic algorithms are usually randomly generated to form the generation. Genetic algorithms are used when traditional methods face obstacles, especially when the objective function is nonlinear and contains real variables. They are able to recognize the best solution, when they find it, but they don't know how they reach it.

This paper presents a modelling technique of the cutting forces resulting when milling improved AISI 1045 using genetic algorithms.

It is a well known fact that milling is a commonly process used in industry, therefore this machining process is thoroughly studied by researchers. The study and modelling of cutting forces lead to a better planning of the cutting process and also to an accurate estimation of other process parameters such as tool life, tool wear etc.

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2. LITERATURE REVIEW REGARDING THE USE OF GENETIC PROGRAMMING IN MODELLING AND OPTIMIZATION OF CUTTING PROCESSES

Nowadays a lot of researchers study modelling processes and try to optimize the milling process.

In case of genetic modelling of cutting forces, important approaches are presented in the papers of Milferner [2, 3, and 4]. In their paper Milferner et al. [2] present the development of a cutting force model using genetic equations in the case of ball-end milling process. They use the forces measured from experiments and the genetic programming. In [3], the authors present an acquisition and simulation system for measuring and simulation of the cutting forces when milling with a ball-end cutter. The simulation system is based on genetic algorithms and on the analytical formulation of the components of cutting forces for the ball-end milling cutter. In the end, the authors present a validation model and compare the simulated cutting forces with the measured ones and conclude that there is a similarity between them. In [5], Gallova uses the artificial intelligence tools such as expert systems, genetic algorithms and the principles of the fuzzy systems theory in order to optimize the process parameters and to estimate the cutting forces when milling with a ball-end cutter. Conceição et al. [6] optimized the multi-pass cutting parameter in face milling using genetic search. Saffari et al. [7] used genetic algorithms to optimize the machining parameters to minimize tool deflection in the end milling operation. Patwari et al. [8] describe mathematically the effect of cutting parameters on surface roughness in end milling of medium carbon steel. The mathematical model for the surface roughness has been developed and solved in terms of cutting speed, feed rate, and axial depth of cut. Wang et al. [9] used genetic simulated annealing for determining optimal machining parameters in case of multi-pass milling. Onwubolu [10] proposed a new optimization technique based on Tribes for determination of the cutting parameters in multi-pass milling operations such as plain milling and face milling. Chengqiang et al. [11] propose the combination of orthogonal experimental method and the genetic algorithm method when optimizing milling parameters, in order to improve tool life. Azlan Mohd Zain et al. [12] present in their paper the capability of genetic algorithm (GA) technique to obtain the optimal machining parameters when milling with an uncoated carbide (WC-Co) tool in order to minimize the surface roughness value. In [13] E. Rivière-Lorphèvre et al. set out different methods to retrieve cutting parameters for several cutting force models, using the least square fitting method and the genetic algorithms. The GA's are tested on nonlinear cutting forces models. The optimization methods are validated using both simulated and measured cutting forces.

3. EXPERIMENTAL CUTTING FORCE MEASURING

The milling investigations were carried out on a CNC machining centre, FIRST MCV 300, with three axes. The measurements were made with a Kistler dynamometer fixed on the machine tool table. The workpiece is mounted on the dynamometer. The signals received by the dynamometer are transmitted through the amplifier, Multichanel Type 5070, on the acquisition board (PCIM-DAS1602/16) installed on the PC. The program used for data acquisition is DynoWare Type 2 825.

The workpiece material used for the experimental tests was a 173 mm length, 85 mm width, and 35mm high piece of steel. The workpiece was initially tested in order to establish the material out of which it is made. There were performed two types of tests, namely: a spectrometry test for establishing the chemical composition, and a test of hardness measuring. Spectrometry test was performed using a spark optical emission spectrometer; called SPECTROMAXx.The test for hardness measurement was performed using a Shimadzu HSV30 device. After conducting the tests it has been established that the workpiece material is improved AISI 1045 having the chemical composition and hardness given in Table 1.

The used cutting tool, CoroMill R 365-080Q27-S15M, and cutting tool insert, R365-1505ZNE-PM 4230, were manufactured by Sandvik Coromant and have the chracteristics given in Fig. 2 and Tables 2 and 3.

Table 1

Chemical composition and hardness of the improved AISI 1045

Material	Chemical composition	Hardness
Improved AISI 1045	98.2% Fe 0.59% Mn, 0.513 % C, 0.387% Si, 0.128% Cu, 0.107% Cr, 0.099% Ni, 0.047% Se, >0.019% N, 0.013% S, 0.011% Co 0.0091% P, 0.0072% As, <0.0070% Ta, 0.0059% Mo, 0.0057% Pb, 0.0055% Sn, 0.0054% Sb, 0.0049% Zn, 0.0046% Al, 0.0020% Ca, <0.0020% Ce, <0.0015%Bi, <0.0015% Zr, 0.0013%Nb, <0.0010% V, <0.007% W 0.0007% Ti, 0.0007% La, <0.0002% B	461 HV-Vickers measured hardness

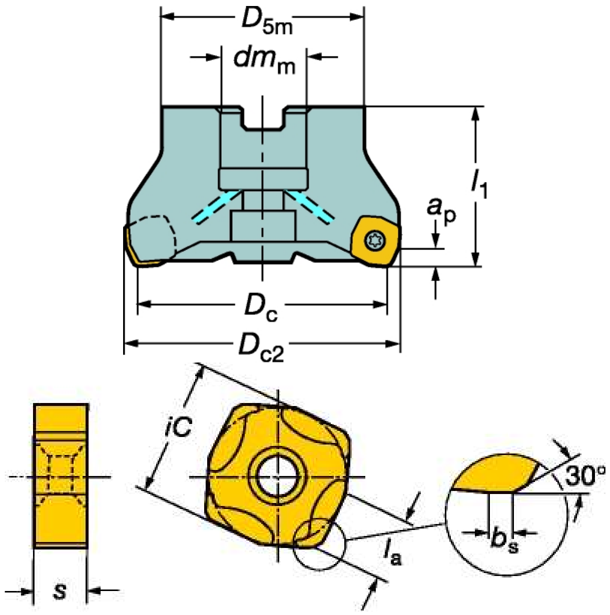

Fig. 2. CAD drawing: *a.* cutting tool, *b.* cutting tool insert [14].

Table 2

Cutting tool technical data [14]

Parameter	Value
Weight	1.3
D_c	80
D_{c2}	86.7
D_{5m}	64
d_{mm}	27
l_1	50
$a_{p\ max}$	6
Max_rpm	11500
κ_r	65

Table 3

Cutting tool inserts technical data [14]

Parameter	Value
Weight	0.014
Size	15
$a_{p\ max}$	6
i_C	15
l_a	6.4
s	5.66
b_s	1.5

The experimental plan was chosen according to Taguchi's Method. Taguchi's Method in industrial practice is a method that seeks to help researchers to obtain faster and cheaper the best results by performing the experiments. This method is based on the orthogonal factorial plan, see Fig. 3. The method consists in defining the process objective, or more precisely defining a target value which measures the process performance; determining the design parameters which affect the process, and establishing the levels of variation of these parameters.

Number of Levels	Number of Parameters (P): 2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31
2	L4	L4	L8	L8	L8	L8	L12	L12	L12	L12	L16	L16	L16	L16	L32	L32	L32	L32	L32	L32	L32	L32	L32	L32	L32	L32	L32	L32	L32	L32
3	L9	L9	L9	L18	L18	L18	L18	L27	L27	L27	L27	L27	L36	L36	L36	L36	L36	L36	L36	L36	L36	L36								
4	L'16	L'16	L'16	L'16	L'32	L'32	L'32	L'32	L'32																					
5	L25	L25	L25	L25	L25	L50	L50	L50	L50	L50	L50																			

Fig. 3. Orthogonal matrix [15].

Table 4

Experimental plan (Taguchi Method)

Exp. No.	Parameter 1	Parameter 2	Parameter 3
1	1	1	1
2	1	2	2
3	1	3	3
4	1	4	4
5	2	1	2
6	2	2	1
7	2	3	4
8	2	4	3
9	3	1	3
10	3	2	4
11	3	3	1
12	3	4	2
13	4	1	4
14	4	2	3
15	4	3	2
16	4	4	1

Table 5

Experimental plan, average and maximum measured cutting forces [N]

Test	a_p	f_z	v_c	Average measured cutting forces [N]			Max. measured cutting forces [N]		
				F_x	F_y	F_z	F_x	F_y	F_z
1	0.5	0.08	150	–17.4991	–21.8793	107.604	89.6301	83.9539	125.061
2	0.5	0.092	165	–26.5493	–72.7621	64.06962	107.208	140.259	88.1195
3	0.5	0.105	181.5	–32.1633	–57.7599	83.2857	120.438	138.428	109.497
4	0.5	0.121	199.6	–38.6642	–84.2418	78.94135	138.748	166.901	99.9756
5	0.63	0.08	165	–33.92627	–70.5911	78.74032	124.146	159.073	102.539
6	0.63	0.092	150	–37.5438	–89.3923	74.46291	144.699	182.327	108.078
7	0.63	0.105	199.6	–13.64	–93.4657	97.43377	194.55	199.036	116.547
8	0.63	0.121	181.5	–33.2112	–89.5799	83.90361	194.183	219.589	124.741
9	0.78	0.08	181.5	–45.5093	–80.3299	120.2731	170.151	187.134	144.47
10	0.78	0.092	199.6	–54.3224	–108.322	86.64886	195.282	220.505	123.688
11	0.78	0.105	150	–52.7918	–116.676	103.8513	199,036	240.509	130.892
12	0.78	0.121	165	–73.9527	–129.45	117.5149	234.65	279.465	149.918
13	0.97	0.08	199.6	–60.7862	–117.021	122.0013	216.751	254.929	144.241
14	0.97	0.092	181.5	–108.773	–226.366	153.2461	379.623	456.116	197.205
15	0.97	0.105	165	–88.9186	–165.489	115.5525	282.852	333.298	162.094
16	0.97	0.121	150	–72.4686	–121.55	85.3426	208.220	245.587	133.295

After setting the parameters and their levels the suitable array of experiences from the orthogonal matrix can be also chosen, Fig. 3. In our case the experimental matrix has three parameters, each parameter having 4 values, resulting 16 tests, as shown in Table 4.

The cutting parameters and average and maximum measured cutting forces are presented in Table 5.

4. GENETIC ALGORITHMS

The GA's include a set of individual elements represented in the form of binary strings, the so called population, and a set of biological operators defined on the population. With the help of the operators, the GA's can manipulate the most promising strings in order to seek the best solutions (Fig. 4). The goal that needs to be accomplished is characterized by a fitness function. In genetic programming, the chromosomes are functions represented by trees in reverse Polish notation. The main steps followed are similar to evolutionary algorithms: selection, crossover, mutation, see Figs. 5 and 6 etc.

As mentioned before, the main elements that allow the analogy between the search problems and natural evolution are:

- chromosomes, an ordered set of elements called genes. The values of genes determine the characteristics of an individual;
- the fitness function: every individual of a population is more or less adapted to that environment. The fitness function is a measure of adaptation to the environment. The purpose of evolution is that all individuals can reach a fitness environment;
- generation is a stage in the evolution of a population. If we consider the development as an iterative process in which a population changes into other populations, then the generation is an iteration of that process.

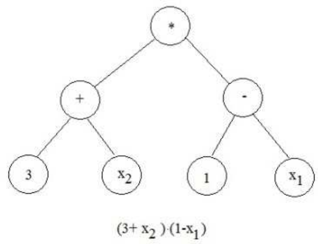

Fig. 4. A simple program in GP.

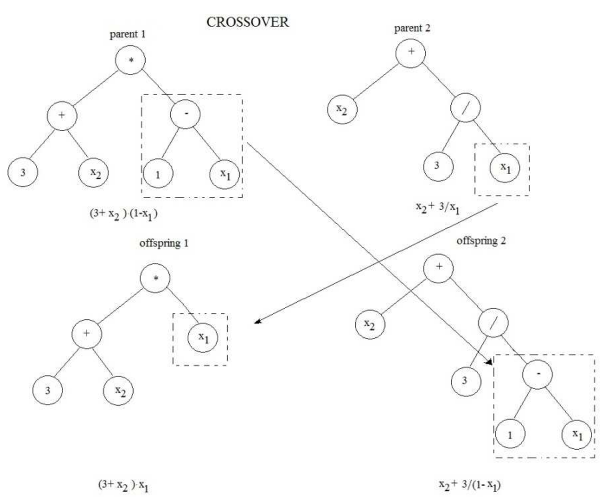

Fig. 5. The Crossover operator in GP.

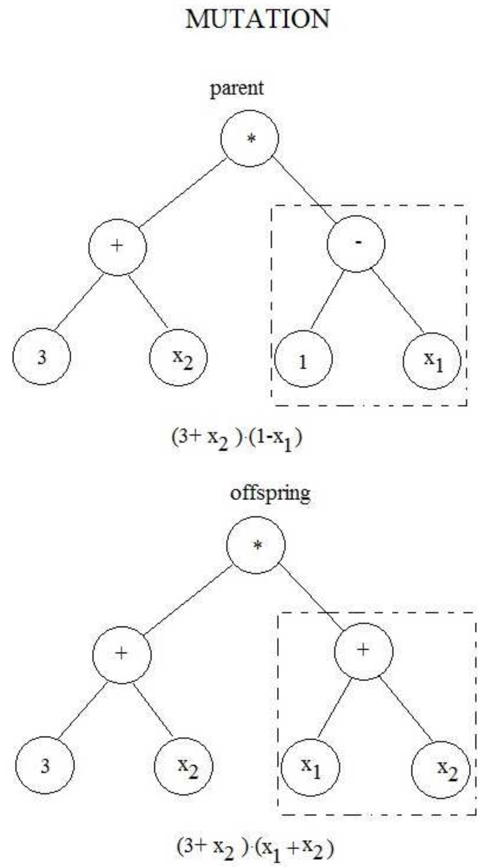

Fig. 6. Mutation in GP.

- crossover allows information combining from two or more parents in order to generate one or more offspring;
- mutation is the process of genes alternation in order to ensure population diversity;
- population: is built up of individuals living in an environment in which they must adapt;
- reproduction: the process of passing from one generation to another. The individuals of the new generation inherit characteristics from their parents, but can acquire also new ones as a result of mutation processes, which have a random character;
- selection: the process of natural selection and has as a result the survival of the individuals with higher fitness.

When using a genetic algorithm it is required to establish in advance:

- the stopping criterion;
- size and the initializing method of the population (population size can be fixed or variable);
- fitness function (the user builds up the function that expresses the degree of adequacy to the environment starting from the objective function and including the problem constraints);
- mechanism of crossover so the parents can generate one or more offspring;
- mechanism of mutation that provides the elements disturbance;
- mechanism for selecting parents and survivors;
- encoding mode (specify how each configuration of the search space is associated with a chromosome).

5. GENETIC MODELLING AND RESULTS

The genetic programming (GP) is an evolutionary method applied to a population of programs in order to achieve a predefined objective usually characterized by a fitness function [1]. The most common usage of fitness function is minimization of the objective function given by a fitness function. If the objective is maximization of the function $f_{fitness}$, simply we can consider the minimization of the function $g_{fitness} = -f_{fitness}$ as goal of the GP method.

In GP, the chromosomes are functions represented by trees in inverse Polish notation. The main steps in GP algorithms are similar to evolutionary algorithms: selection, crossover and mutations. We must remark that all these genetic operators act on trees and sub-trees, different from other evolutionary algorithm where chromosomes are represented by linear sequence of genes.

The main steps in GP are described in what is following [17]. A first population of individuals is created using a random generator (usually uniform distribution). Each individual from population is evaluated according to fitness function. Using the fitness function, the selection operator selects the pairs of individuals (according to selection mechanism: roulette, tournament, stochastic sampling, etc.) in order to apply the crossover operator to create new individuals. The less performing individuals are discarded and the best individuals are grouped in a new generation. Mutations are performed in order to prevent the premature convergence and elitism disadvantages. The population is evaluated again and the loop continues until stop conditions are fulfilled. The stop condition can be a predefined number of iterations or a number of steps (three or four generation) that cannot produce an improvement of fitness for the best individual from population.

There are few software tools that are used for GP: GPLAB, GPdotNET, GPTIPS, GP-OLS and also specialized software tools (PolyLX, texture analysis for petrol). An interesting extension of GP is the combination of more genes represented by trees in a linear fashion and optimization of individuals in two stages: optimization of each gene and optimization of the linear combination (linear regression) [2]. The optimal weights in linear model are obtained by ordinary least squares to regress the genes versus the output data [2]. In our application, we used the software GPTIPS [2, 17]. Practically, the nonlinear model is modelled by a pseudo-linear model with nonlinear genes.

In our application we are looking for a function of type:

$$F_{x,y,z,\,steel} = g(a_p, f_z, v_c) = \sum_{k=1}^{N_g} b_k \cdot g_k(a_p, f_z, v_c)\,. \quad (1)$$

In order to compute g_k and b_k, $k = 1\ldots n$ (n is the maximum number of genes) we use a set of terminals and operators [1]:

$$T = \{a_p, f_z, v_c, RA\}, \quad (2)$$

$$F = \{+,-,*,/,exp\}. \quad (3)$$

In terminal set, RA is a random value in the range [−10.0, +10.0].

6. EXPERIMENTAL RESULTS:

We used a population with 200 individuals, 1 000 generation, maximum number of genes 6 and maximum depth of the tree set to 9. These optimal values are set experimentally in order to find an acceptable error for model for a shortest formula (1) for this overall model.

Even the formulas are enough complicated, the results are very good. The measure error for fitness function is chosen to be RMS error (*Root Mean Square error*), measure of the differences between values predicted by a model and the observed values:

$$RMS_e = \sqrt{\frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{n}}\,, \quad (4)$$

where $\hat{y}_i$ is the estimated value, y_i is the observed value and n the number of samples.

The convergence of the GP is fast enough and a very good result is achieved after maximum 1 000 generations (Fig. 7).

The fit between data and model is given in the next pairs RMS_e and the corresponding formula. In the formulas, y is corresponding to F_x, F_y and F_z variables meanwhile (x_1, x_2, x_3) are the corresponding variables to a_p, f_z, and v_c. We will have six pairs of figures, corresponding to average and maximum values (Figs. 8, 10, 12, 14, 16, and 18) accompanied by the corresponding function forms obtained by GP (Figs. 9, 11, 13, 15, 17, 19).

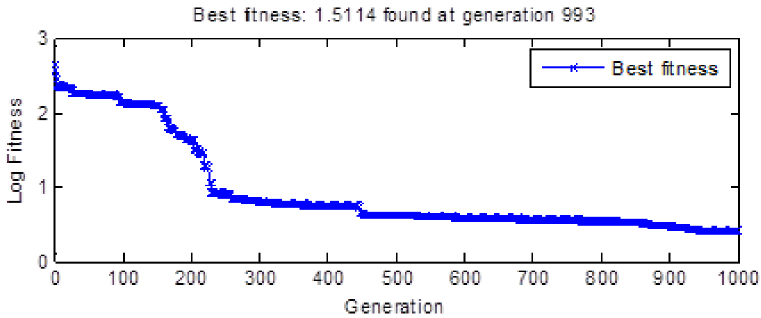

Fig. 7. Convergence of the algorithm [2] for F_z, the case of maximum values.

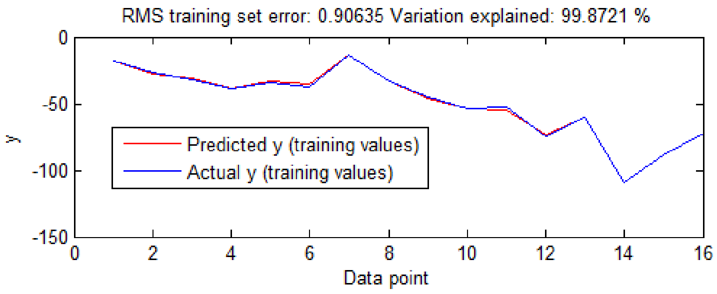

Fig. 8. Steel, average values, RMS$_e$, F_x.

$$\begin{aligned}
y = {} & 3778.0\,x_2 - 235.0\,x_1 - 120.3\,x_3 + \frac{235.0\left(e^{2x_1+2x_2-\frac{0.05332\,x_3}{x_1}}\right)}{x_1+x_2-x_3+1.445} + \frac{407.0\left(x_2+e^{x_1+x_2-1.445}\right)}{3.383\,x_1+3.383\,x_2-7.21} + \\
& \frac{2838.0\,(x_1+2\,x_2)}{x_2+1.445} - \frac{7890.0\left(x_2-\frac{\frac{2x_1+x_2}{x_2+1.445}+\frac{5.544\,x_2}{x_3}+1.445}{x_3}\right)}{x_1+x_2+\frac{3.383}{x_3}-\frac{0.5912\,x_2\left(0.1374\,x_2+0.1374\,e^{1.938-x_2}\right)}{x_1}} + \frac{235.0\left(0.8196\,x_3+e^{x_2+1.445}-12.45\right)}{x_2+1.445} - \\
& \frac{120.3\,(x_3+5.544)}{e^{2x_1-x_2+3.383}+\frac{0.1804\,x_3+1.164}{x_1^{2}\,(0.1804\,x_3-3.383)}} - \frac{\left(5.186\cdot 10^{6}\right)x_2}{2\,x_2+0.6822\,x_3+\frac{x_2+x_3}{\frac{x_1+4.828}{x_2+1.164}+1.164}-\frac{x_2}{x_2+\frac{0.3168\,x_2}{x_1\,x_3\,(0.1086\,x_1-x_2)}}-1.164} - \\
& \frac{795.0}{x_3} + \frac{2838.0\,e^{x_2+2.161}\,(x_2+0.3121)}{x_1+0.9289} - \frac{\left(1.491\cdot 10^{6}\right)\left(x_2-\frac{5.383\,x_1+x_2+\frac{3.415}{x_3}+1.53\cdot 10^{-5}}{x_1-1.18\,x_3+e^{-\frac{5.544}{x_3}}}\right)(x_2-3.383)}{x_3} - \\
& 7081.0
\end{aligned}$$

Fig. 9. Steel, average values, formula for F_x variable.

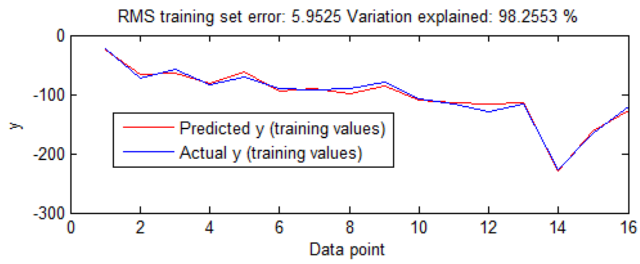

Fig. 10. Steel, average values, RMS$_e$, F_y.

$$\begin{aligned}
y = {} & 0.06636\,x_1 - 7995.0\,x_2 + 737.3\,x_3 - 0.03318\,e^{x_2\,(e+9.336)} + 0.03318\,e^{x_1-x_3-x_1x_2+x_2x_3} + \\
& 231.5\,e^{x_1} + \frac{0.03318\left(\frac{x_3-4.269}{x_2}-4.269\right)}{x_2} - 865.1\,x_2\,(2\,x_1 - x_3 + 9.242) - 0.03318\,x_1\,x_3 - \\
& 57.87\,x_2\,(x_1 - x_3) + 1810.0\,x_2\,(e - 2\,x_3 - 2\,x_1 + 2\,e^{x_1} + 1) - 865.1\,x_2\,(2\,x_1 - 9.242\,x_2 - x_3 + 9.242) - \\
& \frac{102.8\,(x_3-4.269)}{x_2} + \frac{573.1\,x_1}{x_1-x_2} + \frac{1.39\,(1.179\,x_1+0.7449\,x_2-x_3)}{x_2^{3}\,(x_2+x_2^{2}\,(x_1-x_2)+9.301)} - \frac{0.001422\left(e^{e-x_1}-x_3+\frac{1}{x_1\,e^{4.269\,x_2}}\right)(x_1+x_3+9.358)}{x_2^{2}} - \\
& \frac{57.87\left(e^{x_1}-x_3+\frac{x_2}{x_1}+\frac{1}{x_2^{2}\,(x_2+9.253)\left(x_1-0.7918\,x_3+\frac{1}{x_2}\right)}\right)}{x_2^{2}\,(x_2+9.336)} - 0.03318\,x_2\,(e^{x_1} + x_1\,x_3)\,(x_2 + 0.2408\,x_3 + 13.39) - \\
& \frac{0.05956\,(x_3-e^{x_1})\left(x_3-x_1+\frac{9.242\,x_2}{x_1}\right)}{x_2\left(\frac{x_1}{x_3-9.301}-x_2+4.802\right)} - 2660.0
\end{aligned}$$

Fig. 11. Steel, average values, formula for F_y variable.

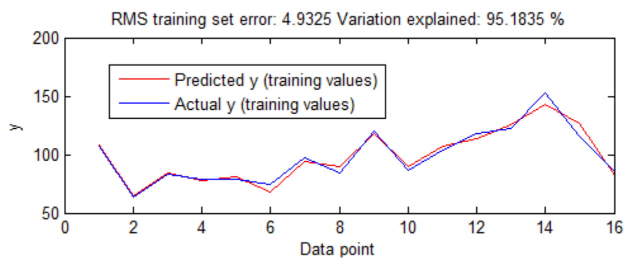

Fig. 12. Steel, average values, RMS$_e$, F_z.

$$y = 109.0\,x_3 - 13577.0\,x_2 - 3973.0\,x_1 + 338.5\,c^{e^{-7.689\,x_2\,e^{x_2}}} + \frac{3418.0}{e^{x_2}} - 1104.0\,c^{x_1^{\,2}} + 3418.0\,e^{x_2} + 338.5\,x_2\left(2\,x_1 + 2\,x_2 + x_3 - (x_2 - 1.588)^2 - 7.154\right) + 0.9541\,(4.215\,x_3 - 31.47\,x_1\,x_2)\,(x_2 - x_2\,e^{x_2}) - \frac{0.9541\left(c^{x_1} - 1.574\,x_2\,c^{3\,x_2} + \frac{x_1}{x_2 - e^{x_1}} + 1.588\,c^{x_2}\,(x_1 - 1.588)\right)}{x_1 + 2\,x_2 - e^{x_2} - x_2\,(x_2 - 1.588)} - \frac{1103.0\,(2\,x_1 + x_2 - c^{x_2} - x_1\,(x_2 - 1.588))}{e^{x_1} - x_2 + x_2\,(x_2 - 1.588)} + 115.7\,e^{x_2}\,(1.516\,x_2\,e^{x_2} - x_3\,e^{x_2}) - \frac{1107.0\,x_1}{2\,x_1 + x_2 - c^{x_1} + 1.516} - 338.5\,(x_1 - x_2)\,(e^{x_1} - 2\,x_2 + 3.175) - 1103.0\,e^{x_1}\,(2\,x_2 - e^{x_1}) + 1714.0\,x_2\,e^{x_2} - \frac{2982.0\,x_1}{2.318\,x_1 + 2.318\,x_2 - 1.318\,e^{x_1}} - 0.9541\,x_1^{\,2} + 3309.0\,x_2^{\,2} + \frac{0.9541\,x_2\,c^{\frac{5.59}{x_3}}\,(x_1 - 7.603)}{x_3} - 5382.0$$

Fig. 13. Steel, average values, formula for F_z variable.

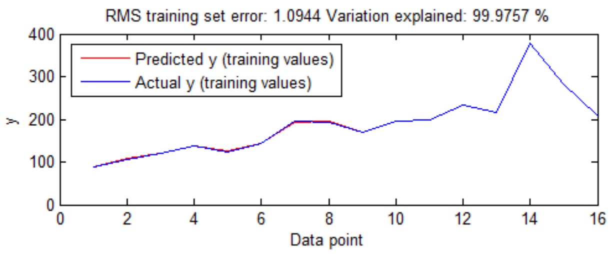

Fig. 14. Steel, maximum values, $\mathrm{RMS_e}$, F_x.

$$y = 256.4\,x_1 - 5161.0\,x_2 - 7.802\,x_3 - 125.8\,e^{8.317\,x_2} - 256.4\,e^{x_2} + 2132.0\,x_1\,x_2 - 426.0\,x_2\,x_3 - 341.2\,x_2\,e^{8.317\,x_2} - 0.001769\,(x_3 - x_3\,(x_1 - x_2))\,(8.317\,x_2 + x_3 - (x_1 - x_2)\,(x_2 + 3\,x_3)) + 256.4\,x_2\,(x_1 + 8.317\,x_1\,x_2 + 8.317) - \frac{138.4\,(8.317\,x_2 + x_3 - x_2\,x_3)}{x_1 - x_3 + 10.32\,x_2\,x_3 + 8.317} + 341.2\,x_1^{\,2}\,x_2 - 202.8\,x_2^{\,2}\,x_3 + \frac{125.8\left(-8.317\,x_1\,x_2^{\,2} + 8.317\,x_2 + x_3\right)}{x_1 - x_3 + 10.32\,x_2\,x_3 + 8.317} - 2581.0\,x_2^{\,2} + 256.4\,x_2\,(x_2\,x_1^{\,2}\,8.317 + 2\,x_3) + 0.003538\,x_2\,x_3\,(2\,x_3 - 1.427) + \frac{69100.0\,(9.317\,x_1 + 8.317\,x_2)\left(x_1^{\,2} + 8.317\,x_2^{\,2} + 70.17\,x_2\right)}{(98.71\,x_1 - 1.427\,x_3 + 23.74)\,(1.427\,x_3 - 1.427\,x_1 + 13.3)} + 1051.0$$

Fig. 15. Steel, maximum values, formula for F_x variable.

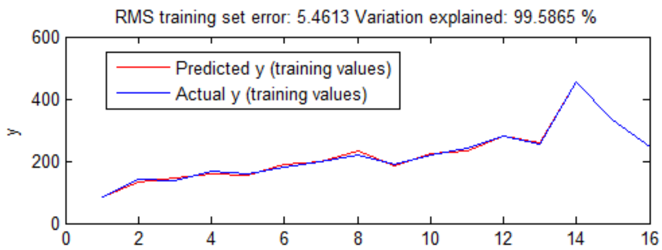

Fig. 16. Steel, maximum values, $\mathrm{RMS_e}$, F_y.

$$y = \frac{5.283\cdot 10^5}{\frac{9.454\,x_2}{e^{e^{\frac{x_2}{c^{x_2}}}}\,(2\,x_2 + e^{x_2})}} - 1047.0\,e^{4\,c^{x_2} - 2\,x_2} + 50377.0\,x_2\,e^{5.604 - 2\,c^{x_2}} + \frac{1047.0\,x_3}{e^{x_2} + e^{x_2} + \frac{x_2}{c^{x_2}}} + \frac{(5.283\cdot 10^5)\left(e^{c^{x_2}} - e^{x_1^{\,2}\,x_2} + \frac{c^{c^{x_2}}}{x_2}\right)}{x_3} - \frac{97900.0\,c^{e^{e^{\frac{c^{c^{x_2}}}{x_3}}}}}{x_2\,(x_2 - x_1 + x_3)} - \frac{18.2\,x_3\,e^{2\,x_2}\left(x_2 + e^{x_2 + \frac{x_2}{e^{x_2}}}\right)}{x_2} + \frac{13.97\,x_1\,e^{\frac{c^{x_1}\,c^{x_2}}{x_2\,x_3}}\left(x_3 + 2\,e^{c^{c^{x_2}}} + 9.419\right)}{x_2\left(e^{e^{x_2}} + e^{x_2} + e^{c^{x_2}}\right)} - 3.624\cdot 10^5$$

Fig. 17. Steel, maximum values, formula for F_y variable.

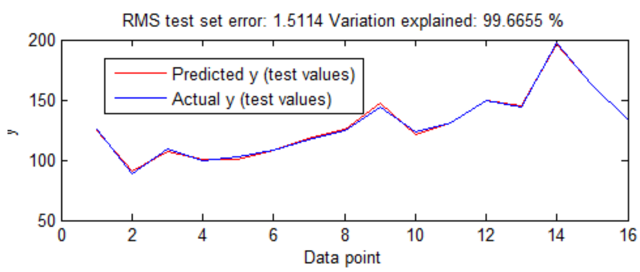

Fig. 18. Steel, maximum values, $\mathrm{RMS_e}$, F_z.

$$y = 283.5\,x_2 - 8457.0\,x_1 - 2137.0\,x_3 - \frac{285.9}{e^{\frac{36.93\,x_1\,x_2\,(x_1^2+x_1)}{x_3}}} + 216.7\,x_3\,\left(e^{\left(9.775\cdot 10^{-5}\right)x_3 - 0.0001955\,x_3^2} + e^{-18.38\,x_1} + 9.958\right) +$$
$$83.73\,x_1\,x_3 + 8.524\,x_1\,(x_3^2 - x_3 + x_1) - \frac{523.2\,(x_1 + (x_1+4.617)\,(2\,x_1+x_3+9.958))}{9.958\left(2.11\,x_1 - \frac{x_2}{x_1}\right)(x_3-9.958) - 99.16} - 0.48\,x_1^3 +$$
$$8.524\,x_1^4 - 0.03874\,x_3^2 + 1066.0\,x_2\,e^{\frac{x_3\left(2\,x_3 - x_3^2\right) + 18.41\,x_2\,(x_1+2\,x_3)\left(5\,x_3 + \frac{x_3}{x_1}\right)}{e^{19.92\,x_1}}} + 8.764\,x_1\,(x_3 - x_3^2) -$$
$$0.24\,x_1^2\,(x_1 - 10\,x_3) - 1285.0$$

Fig. 19. Steel, maximum values, formula for F_z variable.

Very few papers deal with GP applied discovering of formulas that describe the cutting force during a milling process. In fact, only one paper is known [2] by the best knowledge of the authors. If we use a single gene, the convergence of population is considerable slow; the number of populations is considerable increased in order to achieve a good performance. Even in this case, the performance is not as good as in the case of multiple gene regression but the formula is simple in comparison with multiple gene regression. The saturation is present around the 5 000 generation and the fitness value doesn't decrease even at 15 000 generation.

7. CONCLUSIONS

In this paper, the authors accomplished a thorough research on the use of genetic algorithms in modelling the cutting forces resulting in the milling process. The analysis of this research revealed the following:

- it demonstrated that the use of genetic algorithms is modern and suitable for modelling the cutting forces obtaining suitable results similar to real ones;
- modelling results using genetic algorithms and artificial neural networks indicate that output representing the cutting forces can be predicted with a very small error of the order of 10^{-4};
- genetic algorithms have a very good learning power, their accuracy increasing with the number of learning data sets;
- by modelling with genetic algorithms it has been observed that if a single gene is used, then the population convergence is considerably slower;
- to achieve a better performance of the genetic algorithm it is necessary to increase considerably the number of populations. Even in this case, one could not get as good performance as in the use of multiple regression. The only advantage would be that they would get a simpler formula. Saturation occurs at around 5 000 generations but does not diminish the value or suitability to the generation number 15 000.
- even this method of modelling is mostly used in optimization of cutting process, it proved to be a flexible approach and through introduction of modeling with genetic algorithms in studying the cutting forces very closed to reality models were obtained that bring original contribution to the dataset and the material used.

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