International Journal of Scientific Engineering and Technology (ISSN : 2277-1581)
Volume No.4 Issue No.3, pp : 207-211 01 March. 2015

Research on Optimization of Plunge Centerless Grinding Process using Genetic Algorithm and Response Surface Method

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***Abstract:* This paper presents the research on optimization of plunge centerless grinding process when grind 20X – carbon infiltration steel (ГОСТ standard - Russia) to achieve minimum of roundness error value. The input parameters are center height angle of the workpiece (β), longitudinal grinding wheel dressing feed-rate (S_{sd}), plunge feed-rate (S_k) and control wheel velocity (v_{dd}). Using the result of 29 runs in Central Composite Design matrix to given the second order roundness error model. Genetic algorithm and Response surface method were used to focus on determination of optimum centerless grinding above parameters for minimization of roundness error for each methods.**

Keywords: Plunge centerless grinding, optimization, optimization, genetic algorithm, response surface method, roundness error, 20X steel.

1. INTRODUCTION

Centerless grinding is widely used in industry for precision machining of cylindrical components because of its high production rate, easy automation, and high accuracy. 20X - carbon infiltration steel is a common alloy steel that is usually used in mechanical engineering using centerless grinding process.

To improve the centerless grinding process, it is necessary to optimize roundness errors, the most critical quality constraints for the selection of grinding factors in process planning.

Researches on the optimization of centerless grinding process were published by many authors: Minimizing the roundness errors of workpiece by selecting the optimization levels of control wheel speed, feed rate and depth of cut [1]. Minimizing the roundness error of workpiece and carrying out the regression analysis to model an equation to average out roundness error [2]. Predicting the set-up conditions to analyze the dynamic and geometrical instabilities, making it possible to study the influence of different machine variables in stability of the process [3]. Minimizing the lobing effect by developing a stability diagram for workpiece and thereby selecting the grinding parameters and having found out that the characteristic root distribution of the lobing loop is periodic[5]. Investigating the workpiece roundness based on process parameters by both simulation and experimental analysis and finding out that a slower worktable feed rate and a faster workpiece rotational speed result in better roundness error [6]. Minimizing the roundness error of workpiece by selecting the optimization levels of dressing feed, grinding feed, dwell time and cycle time [7]. Minimizing the roundness error of workpiece by selecting the optimization range of the center height angle [8]. Giving a method of how to select the optimal stable geometrical configuration in centerless grinding [9]. Giving an algorithm for providing the optimum set-up condition [10]., etc.

This paper presents the research on the optimization of plunge centerless grinding process when grinding the 20X-carbon infiltration steel to achieve the minimum value of roundness errors. The input parameters include center height angle of the workpiece (β), longitudinal dressing feed-rate (S_{sd}), plunge feed-rate (S_k) and control wheel velocity (v_{dd}). The computer-aided single-objective optimization, solved by genetic algorithm and response surface method, is applied.

2. EXPERIMENTAL SYSTEM

2.1. Centerless grinding model

Plunge centerless grinding model is illustrated in figure 1. The value of center height angle (β) can be adjusted by the value of A. The relationship between (β) and A in equation 1:

$$\beta = \arcsin\left(\frac{A - R_{ct} - H}{R_{dm} + R_{ct}}\right) + \arcsin\left(\frac{A - R_{ct} - H}{R_{dd} + R_{ct}}\right) \qquad (1)$$

Where, H is the distance from the grinding wheel center, control wheel center to the bottom of the workrest blade.

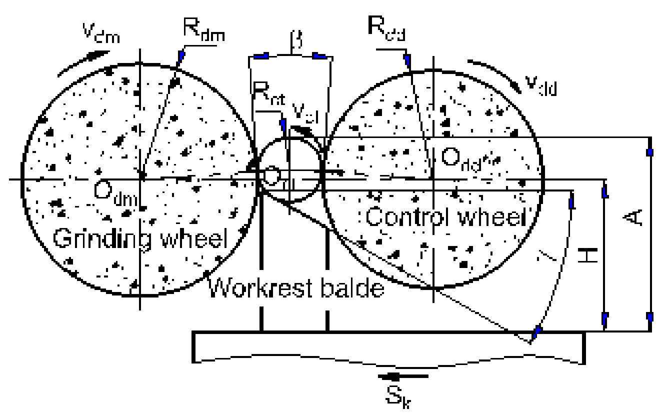

Fig1.Plunge centerless grinding model

2.2. Components

The component material was the 20X-carbon infiltration steel (Fig 2). The chemical composition of experimental component is in Table 1, was supported by specially made workrest blade with a 30^0 angle.

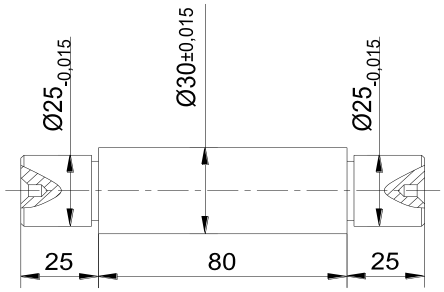

Fig 2. Experimental component

Table 1: Chemical composition of experimental component

C(%)	Si(%)	Mn(%)	P(%)	S(%)	Cr(%)	Ni(%)	Cu(%)
1,02	0,212	0,51	0,018	0,017	0,78	0,017	0,021

2.3. Experimantal machine tool

The grinding experiments were conducted on a M1080B centerless grinder with H = 210 mm, shown in Fig 3.

Grinding wheel: the Al_2O_3 grinding wheel of Hai Duong Grinding Wheels Joint Stock Company, Viet Nam, $Cn80.TB_1.G.V_1$.500.150.305x35m/s.

Control wheel: the standard rubber bonded control wheel of 273 mm x 150 mm x 127 mm dimesions was employed.

Fig3*.Experimantal machine tool*

2.4. Measuring equipment

The roundness error was measured by a dial gage with a precision of 5/10.000. Each design points was measured three times (three ground components). The roundness error response, summarized in Table 3, are the average reading of three consecutive measurements.

3. EXPERIMENT MATRIX

The experiment matrix was conducted under chatter free conditions to keep the grinding wheel speed (34 m/s), the grinding depth (0,05 mm), the depth of dressing (0,01 mm), the spark-out time (1 s) and the coolant flow constant.

In this work, using the central composite design with four input paremeters (β , S_{sd} , S_k , v_{dd}), their levels are presented in Table 2. This experimental matrix with 29 sets; these sets include 16 single-replicated orthogonal factorial points, 8 axial points located and 5 centre points, shown in Table 3.

Table 2. Input parameters and theirs levels

Input parameters	Symbol	Parameter levels				
		-2	-1	0	1	2
Center height angle (^{0})	β	4,8	6,0	7,2	8,4	9,6
Dressing feed-rate (mm/min)	S_{sd}	100	200	300	400	500
In-feed speed (μm/s)	S_k	2	6	10	14	18
Control wheel velocity (m/min)	v_{dd}	18,9	24,25	29,6	34,95	40,3

Table 3. Experimetal matrix

Set	β	S_{sd}	S_k	v_{dd}	$\Delta(\mu m)$	$\Delta^*(\mu m)$
1	1	-1	-1	1	2,67	2.84
2	0	0	-2	0	2,33	2.11
3	-2	0	0	0	2,50	2.28
4	-1	1	-1	-1	3,33	3.46
5	-1	1	-1	1	2,67	2.81
6	0	0	0	0	1,00	1.23
7	-1	-1	1	-1	2,50	2.58
8	1	-1	1	1	3,00	3.05
9	-1	-1	-1	-1	2,17	2.29
10	1	1	1	1	1,00	1.15
11	0	0	0	-2	3,33	3.14
12	-1	-1	1	1	1,83	2.00
13	-1	1	1	-1	2,67	2.76
14	1	1	1	-1	1,17	1.30
15	0	0	0	0	1,33	1.23
16	0	0	0	0	1,00	1.23
17	0	0	0	0	1,33	1.23
18	0	0	0	2	3,33	3.08

19	1	-1	-1	-1	1,50	1.58
20	1	-1	1	-1	2,33	2.45
21	1	1	-1	1	1,83	1.94
22	-1	-1	-1	1	2,33	2.38
23	-1	1	1	1	1,33	1.44
24	2	0	0	0	1,50	1.28
25	0	2	0	0	2,00	1.75
26	0	-2	0	0	2,67	2.48
27	1	1	-1	-1	1,33	1.42
28	0	0	2	0	1,83	1.61
29	0	0	0	0	1,50	1.23

The statistical analysis software Minitab 16 was used to determine the regression coefficients. The roundness error models was developed in the form of non-reduced final equation in terms of coded parameters.

$$\begin{aligned}\Delta &= 1{,}232 - 0{,}25\beta - 0{,}18083S_{sd} - 0{,}125S_k \\ &- 0{,}014167v_{dd} + 0{,}13658\beta^2 + 0{,}22033S_{sd}^2 \\ &+ 0{,}15658S_k^2 + 0{,}46908v_{dd}^2 - 0{,}33375\beta.S_{sd} \\ &+ 0{,}14625\beta.S_k + 0{,}2925\beta.v_{dd} - 0{,}24875S_{sd}S_k \\ &- 0{,}1875S_{sd}v_{dd} - 0{,}1675S_k v_{dd}\end{aligned} \quad (2)$$

The upper model can be used to predict surface roughness at particular design points. The numerical values of predicted responses Δ^* are also summarized in Table 3. The differences between the measured and predicted responses is shown in Figs 4.

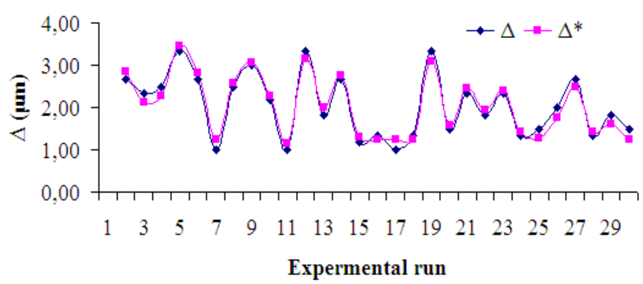

Fig 4. Measured and predicted roundness error

4. OPTIMIZATION

4.1. Using Genetic Algorithm

GAs form a class of adaptive heuristics based on principles derived from the dynamics of natural population genetics. The searching process simulates the natural evolution of biological creatures and turns out to be an intelligent exploitation of a random search. A candidate solution (chromosomes) is represented by an appropriate sequence of numbers. In many applications the chromosome is simply a binary string of 0 and 1.

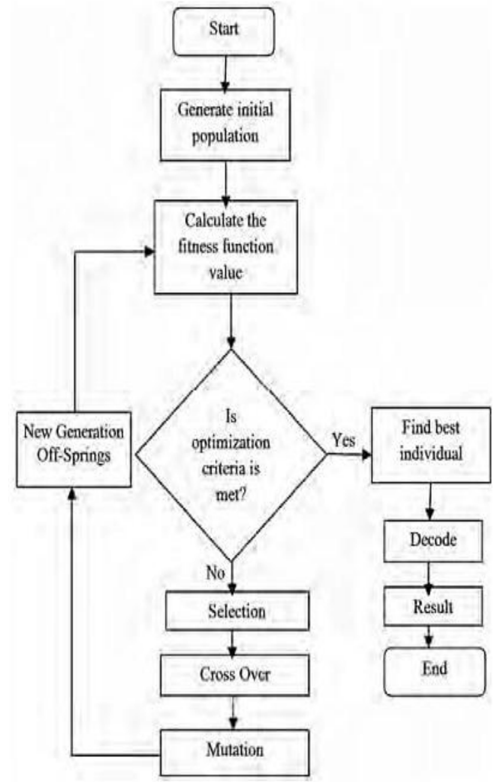

Fig 5. Structure of a general GA

The quality of its fitness is the function which evaluates a chromosome with respect to the objective function of the optimization problem. A selected population of the solution (chromosome) initially evolves by employing mechanisms modelled after those currently believed to apply in genetics. Generally, the GA mechanism consists of three fundamental operations: reproduction, crossover, and mutation. Reproduction is the random selection of copies of solutions from the population, according to their fitness value, to create one or more offspring. Crossover defines how the selected chromosomes (parents) are recombined to create new structures (offspring) for possible inclusion in the population. Mutation is a random modification of a randomly selected chromosome. Its function is to guarantee the possibility to explore the space of solutions for any initial population and to permit the freeing from a zone of local minimum. Generally, the decision about the possible inclusion of crossover/mutation offspring is governed by an appropriate filtering system. Both crossover and mutation occur at every cycle, according to an assigned probabilty.The aim of the three operations is to produce a sequence of populations that, on the average, tends to improve.

Structure of a general GA is illustrated in figure 5.

To get the optimization of β, S_{sd}, S_k, v_{dd} value for minimum the value of roundness error (Δ), objective function Δ can be written:

$$\begin{cases} \Delta = f(\beta, S_{sd}, S_k, v_{dd}) \rightarrow \min \\ \Delta > 0 \\ -2 \le \beta, S_{sd}, S_k, v_{dd} \le 2 \end{cases} \quad (3)$$

Table 4. Genetic algorithm optimization

β	1,9999
S_{sd}	1,9996
S_k	1,0889
v_{dd}	-0,0056
Population	150
Crossover probability	0,25
Mutation probability	0,05
Δ	0,2893

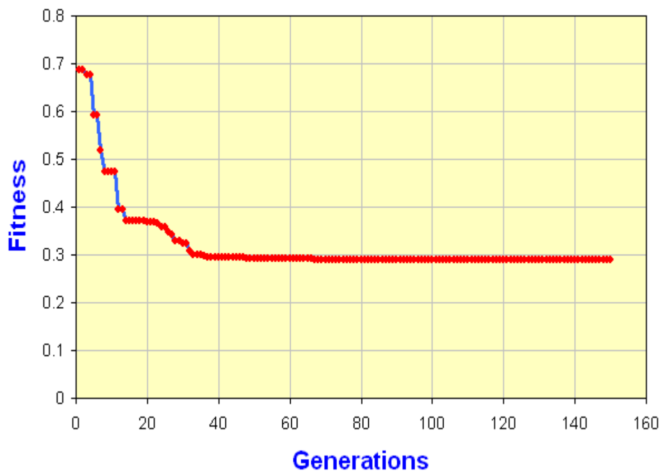

Fig. 6. Genetic algorithm graph

This is performed with an adopted optimization program, developed in Excel [11]; population of appointed size is randomly chosen between the lower and upper values and undergoes a process of evolution in a simulated competitive environment. The latter mechanism consists of tournament selection, linear crossover and non-uniform mutation. Both bit-exchange crossover and bit-flip mutation occur at every cycle, according to assigned probabilities. Optimization has been achieved by determination of three control parameters of the genetic algorithm; the size of the population and the probability values for crossover and mutation, quoted in Table 4. The considered factor ranges relate to the region of interest. The fitness of each individual is evaluated (Fig. 6).

4.2. Using Response Surface Method

In the process of optimization, the goal is to minimize the roundness error (Δ). Minitab 16 software is used to optimize this objective. The optimization graph and numerical values are shown in Figure 7 and Table 5 respectively.

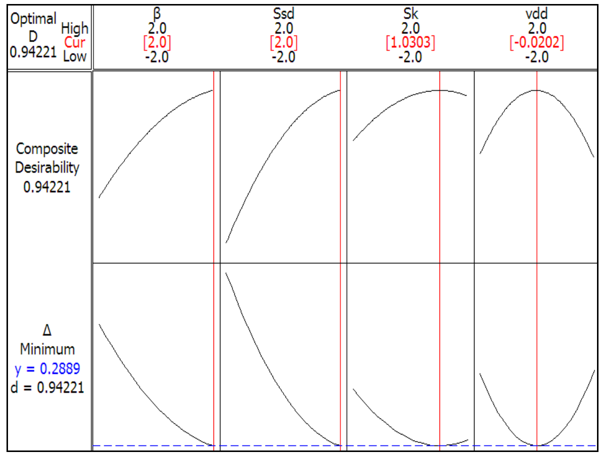

Fig 7. *RSM* graph

Table 5. *RSM* optimization

β	2,0
S_{sd}	2,0
S_k	1,0303
v_{dd}	-0,0202
Δ	0,2889

5. COPARISON FOR GA AND RSM

In put the optimization values of β, S_{sd}, S_k, v_{dd} that done by GA (Tab 4) and RSM (Tab 5) in to equation 2, to get value of roundness error (Δ^*), the result is shown in Table 6. Optimization values of β, S_{sd}, S_k, v_{dd} which are similar for GA and RSM. However, in detail, accuracy of GA is better than RSM

Table 6. *Comparison for optimization of GA and RSM*

METHOD	β	S_{sd}	S_k	v_{dd}	Δ	Δ^*	Difference
GA	1,9999	1,9996	1,0889	-0,0056	0,2893	0.2892	0,0001
RSM	2,0	2,0	1,0303	-0,0202	0,2889	0.2886	0,0003

6. CONCLUSION

- For optimization of plunge centerless grinding process, accuracy of GA is better than RSM

- For the work material 20X-carbon infiltration steel, to achieve the minimum roundness error of the 20X-carbon infiltration steel, the numerical values of β, S_{sd}, S_k and v_{dd} are 9,5999(degree); 499,960(mm/min); 14,3556 (μm/s) and 29,570 (m/min) respectively.

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