Optimization of Cutting Parameters for Surface Roughness in the Ball-End Milling Process Using Genetic Algorithm

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Abstract. The aim of this is to demonstrate the possibilities of applying a genetic algorithm to optimize the input parameters of the ball-*end* milling process when machining hardened steels as a function of the minimum surface roughness. The experimental investigations were carried out using a four-factor experimental design. RSM was used to determine the basic relationship between the input parameters of the process (spindle speed, feed per tooth, axial and radial depth) and the surface roughness. The developed second-order model was used as a reference model for the GA application. The obtained GA model of surface roughness was a function of the goal of the genetic algorithm, which required finding a minimum value of surface roughness Ra. Based on certain optimal values of the input parameters, a confirmation experiment was performed. The measured value of the surface roughness showed a good agreement with the value obtained by GA. The results obtained show the efficiency of the GA application for modeling and optimization of ball-end milling processes.

Keywords: Optimization · Ball-end milling process · Genetic algorithm

1 Introduction

The ball-end milling of hardened steels is increasingly being applied in many industries (automotive, die and mold making, aerospace, etc.). The increase in the use of this machining in the metalworking industry is related to its efficiency, productivity and quality of the machined surface. This machining is particularly interesting for achieving complex surfaces in 3- and 5-axis milling [1]. The cutting geometry of ball-end cutters is very specific compared to other types of milling tools. For the reasons mentioned above, many scientists have been investigating this process over the last decades and have found complex relationships between input variables and output performances of the machining process.

When optimizing systems and machining processes, the selection of the parameters of the machining process is a key task for the success of the machining. The choice of

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machining parameters is usually based on the assessment and experience of people (or production engineers). However, the machining parameters selected in this way do not lead to good results. The reason for this is that the machining process is influenced by many factors that prevent the high performance and quality of the process from being achieved in practice.

Optimization algorithms can be divided into conventional and unconventional algorithms [2]. Unconventional optimization algorithms are mainly based on biological, molecular or neurological phenomena that mimic the metaphor of biological evolution and/or social behavior of different species of living organisms in nature. To effectively mimic the behavior of these species, researchers have developed computer systems that seek fast and robust solutions to complex optimization problems. Examples of these systems are Genetic Algorithm (GA), Simulated Annealing (SA), Particle Swarm Optimization (PSO), Artificial Bee Colony (ABC), Ant Colony Optimization (ACO), etc.

The surface roughness is one of the most important parameters for determining the quality of a product and a factor that has a major influence on production costs. Surface roughness in ball-end milling is influenced by a number of factors: machining parameters (cutting conditions, cutting fluid, and process kinematics), material properties (hardness), cutting tool properties (tool material, tool shape, nose radius, run-out error), cutting phenomena (friction in the cutting zone, cutting force fluctuations, acceleration, chip formation). The correct selection of cutting conditions is very important in ball-end milling due to the complexity of the process. The aim of this paper is to show the possibilities of applying a genetic algorithm to optimize the cutting parameters in ball-end milling process (spindle speed, feed per tooth, axial and radial depth) in the finish processing of hardened steels as a function of the minimum surface roughness.

2 Literature Review

Many researchers have proposed different methods, conventional and unconventional, to determine the optimum values of cutting conditions as a function of the minimum value of surface roughness in various machining processes. A number of studies are concerned with modeling and optimizing surface roughness in ball-end milling.

Dhokia et al. [3] modeled the surface roughness R_a in ball end milling of polypropylene using a genetic algorithm. The experimental tests were performed according to the orthogonal array design L_{16}. The model obtained GA showed good accuracy, as the mean deviation between the calculated and experimental data was less than 8.43%.

Vakondios et al. [4] investigated how the machining strategy affects the surface roughness of a single aluminum alloy. For different machining strategies, the cutting parameters (axial and radial depth of cut, feed rate, inclination angle) were varied for both down and up milling. Mathematical models for surface roughness under different machining strategies were obtained by regression analysis, and their adequacy was verified by ANOVA analysis. The polynomial models obtained are of third order.

Hossain and Ahmad [5] used Response Surface Methodology (RSM) and Adaptive Network- based Fuzzy Interface System (ANFIS) models to predict surface roughness in ball-end milling. The results obtained show that the ANFIS model predicts surface roughness with greater accuracy than Response Surface Methodology.

Sekulić et al. [6] applied Response Surface Methodology (RSM), Genetic Algorithm (GA), and Grey Wolf Optimizer (GWO) algorithm for predicting surface roughness in ball- end milling of hardened steel. The prediction models developed using the nature-inspired algorithms (GA and GWO) showed good possibilities for predicting the surface roughness in ball end milling.

Kuram and Ozcelik [7] investigated the multi-objective optimization in the ball-end micro-milling process. The effects of spindle speed, feed per tooth and depth of cut on tool wear, forces and surface roughness were investigated. The multi-objective optimization was performed using Taguchi-based gray relational analysis to find the optimal combination of process input parameters to obtain minimum values of surface roughness Ra, cutting forces Fx and Fy, and tool wear.

Kumar et al. [8] applied a genetic algorithm to find the optimal values of spindle speed, feed per tooth and depth of cut as a function of the minimum surface roughness Ra. Based on the Box-Behnken design of experiment, a Response Surface Methodology was applied to obtain a model of surface roughness. This model was objective function for Genetic Algorithm. The validation of the experiment with optimally adjusted parameters was confirmed with an error of 8.88%.

3 Experimental Procedure and Results

The procedure for determining the optimum values of cutting conditions as a function of the minimum surface roughness consists of three parts:

1. planning and conducting experiments,
2. finding a suitable model for determining the surface roughness using RSM and ANOVA, and
3. optimizing the cutting parameters using GA.

Experimental tests were carried out in the factory "ELMETAL" Ltd. from Senta and in the Laboratory for conventional machining technologies at the Faculty of Technical Sciences [10].

The tests were performed on a vertical CNC milling machine HAAS VF-3YT. The workpiece material was hardened steel X210CR12 with hardness 58 HRC. Emuge-Franken ball-end milling cutters (type 18771A, d = 6 mm, double-edged solid carbide cutters with TiAlN-T3 coating) were used as cutting tools. The workpiece dimensions were 300 mm × 58 mm × 20 mm. The workpiece was further machined by dividing the work area into 84 fields with the dimensions 15.33 mm × 3 mm. Each field served as a single test point. The surface roughness of the machined surface was measured using the portable MarSurf PS1 instrument.

The input independent parameters were spindle speed, feed per tooth, axial depth of cut and radial depth of cut. The tests were conducted according to a Central Composition Design (CCD), which included 30 experiments. The values of the cutting conditions were defined based on the properties of the workpiece material and the cutting tool as well as the recommendations of the tool manufacturer itself. Each input parameter was varied in five levels. The machining parameters and their levels are listed in Table 1.

Table 1. Machining parameters and their levels.

Parameters	Levels				
Spindle speed, n (min^{-1})	3981	4777	5573	6369	7169
Feed per tooth, f_z (mm/tooth)	0.018	0.024	0.030	0.036	0.042
Axial depth of cut, a_p (mm)	0.04	0.08	0.12	0.16	0.20
Radial depth of cut, a_e (mm)	0.20	0.40	0.60	0.80	1.00

Spindle speed is determined by equation below:

$$n = \frac{v}{2 \cdot \pi \cdot \sqrt{a_p \cdot (d_1 - a_p)}} \tag{1}$$

where v is the cutting speed, a_p is the axial depth of cut and d is diameter of the tool.

The measured values of surface roughness for all 30 experimental points are shown in Table 2.

3.1 Modeling of the Surface Roughness by RSM and Determination of Suitable Model Type Using ANOVA

Response Surface Methodology (RSM) is a set of statistical and mathematical methods useful for modeling and optimizing engineering problems. It is a simple, widely used method for studying the relationship between independent process performance (response) and dependent process input parameters. RSM provides a wealth of information from a small number of experiments. Design Expert Software has been used for statistical processing of experimental data with RSM. The goal of the modeling was to establish the relationship between surface roughness and the input parameters of the ball-end milling process such as spindle speed, feed per tooth, axial depth of cut and radial depth of cut. The adequacy of the models obtained and the significance of the input parameters were determined by ANOVA analysis.

The analysis of variance (ANOVA) shows that the reduced second-order quadratic model is best suited for predicting surface roughness [6]:

$$R_{a(RSM)} = 0.95 - 1.85 \cdot 10^{-4} \cdot n + 1.53 \cdot f_z + 0.26 \cdot a_p - 0.85 \cdot a_e + 5.76 \cdot a_e^2 \tag{2}$$

ANOVA is shown in Table 3. The p-value is lower than 0.05, which proves that the model is considered appropriate at the 95% confidence level. The p-value was calculated for all parameters of the proposed model. Based on the calculated p-values, it can be concluded that the radial depth of cut ae ($p < 0.0001$) has the greatest influence on surface roughness.

Table 2. Experimental results for surface roughness.

Trial No.	Code					Parameters				Measured value R_a (μm)
	x_0	x_1	x_2	x_3	x_4	n (min^{-1})	f_z (mm/z)	ap (mm)	a_e (mm)	
1	1	−1	−1	−1	−1	4777	0.024	0.08	0.40	0.745
2	1	1	−1	− 1	−1	6369	0.024	0.08	0.40	0.305
3	1	−1	1	−1	−1	4777	0.036	0.08	0.40	0.643
4	1	1	1	−1	−1	6369	0.036	0.08	0.40	0.497
5	1	−1	−1	1	−1	4777	0.024	0.16	0.40	0.662
6	1	1	−1	1	−1	6369	0.024	0.16	0.40	0.569
7	1	−1	1	1	−1	4777	0.036	0.16	0.40	0.850
8	1	1	1	1	−1	6369	0.036	0.16	0.40	0.425
9	1	−1	−1	−1	1	4777	0.024	0.08	0.80	3.370
10	1	1	−1	−1	1	6369	0.024	0.08	0.80	3.040
11	1	−1	1	−1	1	4777	0.036	0.08	0.80	3.302
12	1	1	1	−1	1	6369	0.036	0.08	0.80	3.149
13	1	−1	−1	1	1	4777	0.024	0.16	0.80	3.261
14	1	1	−1	1	1	6369	0.024	0.16	0.80	3.116
15	1	−1	1	1	1	4777	0.036	0.16	0.80	3.379
16	1	1	1	1	1	6369	0.036	0.16	0.80	3.113
17	1	0	0	0	0	5573	0.030	0.12	0.60	1.677
18	1	0	0	0	0	5573	0.030	0.12	0.60	1.518
19	1	0	0	0	0	5573	0.030	0.12	0.60	1.571
20	1	0	0	0	0	5573	0.030	0.12	0.60	1.296
21	1	−2	0	0	0	3981	0.030	0.12	0.60	1.926
22	1	2	0	0	0	7166	0.030	0.12	0.60	1.159
23	1	0	−2	0	0	5573	0.018	0.12	0.60	1.334
24	1	0	2	0	0	5573	0.042	0.12	0.60	1.299
25	1	0	0	−2	0	5573	0.030	0.04	0.60	1.324
26	1	0	0	2	0	5573	0.030	0.20	0.60	1.285
27	1	0	0	0	−2	5573	0.030	0.12	0.20	0.245
28	1	0	0	0	2	5573	0.030	0.12	1.00	4.258
29	1	0	0	0	0	5573	0.030	0.12	0.60	1.470
30	1	0	0	0	0	5573	0.030	0.12	0.60	1.471

3.2 Modeling of the Surface Roughness by Genetic Algorithm (GA)

RSM was used to determine the basic relationship between the entered process parameters (spindle speed, feed per tooth, axial and radial depth of cut) and the surface roughness. The developed second-order model served as a reference model for the later application of GA. GA is a meta-heuristic method that mimics the process of natural evolution to find the solution space. This method uses three types of operators: selection, crossover and mutation. The key to selection in the genetic algorithm is the fitness function. GA in the modeling process allows to obtain the required model based on the predefined model shape. The general shape of the reduced second-order model (Eq. 2) was indirectly used as an objective function in ball-end milling process.

The fitness function is defined as:

$$\Delta = \frac{1}{n}\sum\nolimits_{i=1}^{n} \frac{|E_i - G_i|}{E_i} \cdot 100\% \quad (3)$$

where n is the size of sample data, E_i the measured R_a and Gi predicted R_a calculated by GA.

It is necessary to find a minimum value for this function, since in this way one obtains the smallest error of the model obtained by the genetic algorithm in relation to the experimental data. GA model was created by GA Tool in MATLAB using the experimental results from Table 2. The model developed to predict the surface roughness Ra using GA is [6]:

$$R_{a(GA)} = 1.48 - 1.85 \cdot 10^{-4} \cdot n + 4.75 \cdot f_z + 0.79 \cdot a_p - 3.94 \cdot a_e + 8.8 \cdot a_e^2 \quad (4)$$

The predicted values for surface roughness as obtained in GA were compared with experimental values. The model accuracy of the GA model (Eq. 4) was 91.78% [6], which is a good agreement with experimental data.

Table 3. ANOVA for response surface.

Response	R_a						
ANOVA for response surface							
Analysis of variance table [Partial sum of squares - Type III]							
Source	Sum of squares	df	Mean square	F value	p-value prob > F		PC (%)
Model	37.24	5	7.45	140.10	<0.0001	Significant	
A-n	0.52	1	0.52	9.78	0.0046		1.35
B-fz	2.017E−03	1	2.017E−03	0.038	0.8472		0.01
C-ap	2.521E−03	1	2.521E−03	0.047	0.8294		0.01
D-ae	35.19	1	35.19	661.90	<0.0001		91.36
D^2	1.53	1	1.53	28.72	<0.0001		3.96
Residual	1.28	24	0.053				3.31
Lack of fit	1.20	19	0.063	3.93	0.0677	Not significant	3.10
Pure error	0.080	5	0.016				0.21
Cor total	38.51	29					100
	$R^2 = 0.9669$; Adj $R^2 = 0.9599$						

4 GA Based Optimization of Ball-End Milling Parameters

GA allows to obtain optimal values of input parameters based on the previously developed Eq. 4. This equation is an objective function of the genetic algorithm for which it is necessary to find the minimum value of surface roughness. The limits of the range in which the optimal values were sought were determined on the basis of the data in Table 1.

The limits of the range are:

$$3981 \le n \le 7166$$
$$0.018 \le f_z \le 0.042$$
$$0.04 \le a_p \le 0.20$$
$$0.2 \le a_e \le 1.00$$

The optimum values of the cutting parameters and the minimum surface roughness Ra obtained by GA optimization are given in Table 4. Table 4 also shows the comparison between the GA result and the surface roughness value measured after the confirmation test. The good agreement between GA result and measured surface roughness shows the effectiveness of the proposed optimization method.

Table 4. Results of GA optimization.

Optimal values of input cutting parameters					
R_a [μm]		n [min $^{-1}$]	f_z [mm/tooth]	a_p [mm]	a_e [mm]
GA result	0.180	7166	0.018	0.04	0.23
Measured value after confirmation test	0.206				

5 Conclusions

In this paper the application of the optimization GA method for the determination of optimal cutting parameters in ball-end milling process was shown. The objective function was to minimize the surface roughness. For the application GA in the optimization of machining parameters it is necessary to predefine a mathematical model of surface roughness. RSM and ANOVA were used to determine an adequate mathematical model that establishes the basic relationship between the surface roughness and the cutting parameters of the ball-end milling process. The defined second-order model was used as a reference model for the later application of GA. The newly created GA model was obtained using GA Tool from MATLAB. The resulting GA model showed good accuracy in predicting surface roughness. This was an important prerequisite for the further process of determining optimal values of cutting parameters with GA. After determining the optimal values of the cutting parameters, a verification experiment was performed. The measured value of the surface roughness after the verification experiment showed a good agreement with the value obtained previously by the GA optimization procedure.

GA optimization method presented in this paper have a potential to improve the initial process parameters to achieve the minimum value of surface roughness in ball-end milling process with high accuracy, which was clearly verified by the confirmation test.

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