MODELING OF EXTERNAL CYLINDRICAL GRINDING PROCESS USING T1 TOOL STEEL

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Abstract

The selection of the optimal external cylindrical grinding conditions importantly contributes to increase of productivity and quality of the products. The external cylindrical grinding is a method of finishing machine elements surface with an indeterminate blade shape. External cylindrical grinding can process surfaces that require high gloss and precision, although it can also be used to remove large surplus stock. Therefore, multi objective optimization for the external cylindrical grinding process is a problem with high complexity. In this study, an experimental study was performed to improve the productivity and quality of grinding process. By using the experimental date, the surface roughness, cutting force, and vibrations were modeled. To achieve the minimum value of surface roughness and maximum value of material removal rate, the optimal values of external cylindrical grinding conditions were determined by using the combination of Genetic Algorithms (GAs) and weighting method. The optimum values of surface roughness and material removal rate are 0.510 μm and 5.906 mm^2/s, respectively. The obtained optimal values of cutting parameters were a feed rate of 0.3 mm/rev, a workpiece speed of 188.1 rpm, a cutting depth of 0.015 mm, and a workpiece Rockwell hardness of 54.78 HRC. The optimal values of cutting parameters, and workpiece hardness were successfully verified by comparing of experimental and predicted results. The approach method of this study can be applied in industrial machining to improve the productivity and quality of the products in external cylindrical grinding process of the T1 tool steel.

Keywords: External cylindrical grinding, Modeling, Genetic Algorithms, productivity, quality, surface roughness, workpiece Rockwell hardness, cutting force, vibration.

1. Introduction

Machining process in general and the grinding process in particular, the productivity and surface roughness are the two important goals that the engineers and workers always want to aim. Depending on the stages of the grinding process the objective can be productivity or surface roughness, but the desire during the grinding process is to achieve both productivity and surface roughness. The optimal problem of two or more goals is called the multi-objective optimization problem. This is a complex problem containing many boundary conditions and constraints with large search space, so to solve this problem requires an appropriate algorithm.

Many studies have been conducted to investigate the influence of cutting parameters on the surface roughness, cutting forces, vibrations, and material removal rate. The effective evaluation of the optimization process was achieved by rapid-working in-process and post-process measurement systems [1]. A novel modelling schemes and optimization methods for surface roughness was proposed based on evolutionary algorithms in the grinding processes [2]. An available model with single criteria material removal rate was applied to obtain the optimum grinding parameters for silicon carbide grinding process using the particle swarm optimization algorithm [3]. A combination method of the target tree method and the genetic algorithm was used to optimize the grinding process [4].

In multi-objective optimization of grinding process, there are more things that have done with the real application. A better solution technique with scatter search approach was proposed for multi-objective optimization of surface grinding operations [5]. An approach using integrated Genetic Algorithm-Neural Network system was applied to optimize the creep feed grinding process. The aim of this study was determination of the maximal metal removal rate (MRR) and the minimum of the surface roughness (R_a) in creep feed grinding process [6].

An optimization approach based on enhanced Pareto particle swarm optimization algorithm and local climbing optimization technique was proposed to solve the optimization problem in the grinding processes [7]. The ant colony algorithm approach was successfully applied to solve

the optimization problem in the grinding processes [8]. A combination method of genetic algorithm and weighted objective function based on the optimization procedure was proposed to optimize for the surface grinding process [9], to model and optimize the parameters in chemotherapy [10], to focus mainly on optimization technique and engineering application [11], to optimize the part flow time between machines, processing time of the part, throughput of the plant [12].

In this study, a combination method of genetic algorithms (GAS) and weighting methods was proposed to solve the multi-objective optimization problem. The surface roughness function (R_a) and material removal rate function (Q') were selected as the evaluation criteria in grinding process. The constraint functions including cutting force (F_y and F_z), and vibration function (A) were built using experimental data of external cylindrical grinding the T1 tool steel. The achieved results are important bases to select the suitable machining conditions to achieve the highest productivity and the smallest surface roughness in external cylindrical grinding process.

2. Materials and methods
2. 1. Multi-Objective optimization method
2. 1. 1. Multi-Objective optimization process
Fig. 1 described the multi-objective optimization process in the grinding process.
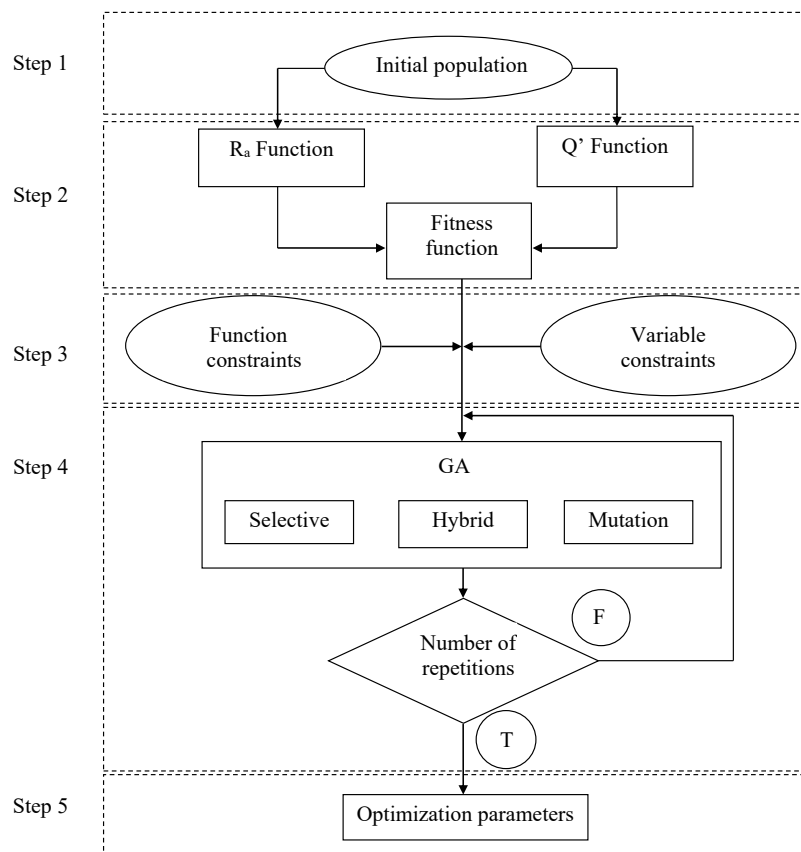
Fig. 1. Block diagram to solve the multi-objective optimization problem for external cylindrical grinding process

The steps to solve the optimization problem were presented as following:
– Step 1. Setting the initial population: The initial values of machining parameters and the hardness of the workpiece material are the initial values of the optimization process.
– Step 2. Determination of objective functions: Surface roughness (R_a) and material removal rate (Q') function are modeled as the single objective functions. The adaptive function was built as a multi-objective function, which is a function of single-objective functions.

– Step 3. Determination of boundary conditions: The boundary conditions include the function constraints and variable constraints. The function constraints in this problem included vibration and force functions, variable constraints are cutting parameters and machining material stiffness.

– Step 4. Solving the optimization problem: This step consists of the selection, the hybridization, and the mutation of the genetic algorithm. The number of iterations to create the best individual among selected individuals to find the optimal parameters.

– Step 5. Obtaining the optimum values.

2. 1. 2. Multi-objective functions

The grinding process is divided into rough grinding and fine grinding. With rough grinding, the greatest productivity is concerned while maintaining a certain surface roughness. With fine grinding, the goal optimization process is to achieve the smallest surface roughness and to ensure the maximum value of machining productivity [6]. Thus, the grinding process needs to satisfy as follows:

– minimum in surface roughness;

– maximum of machining productivity, or maximum of material removal.

Therefore, it is possible to build a multi-objective function by weighting method as by the eq. (1):

$$M = w_1 \cdot \frac{R_a}{R_a^*} - w_2 \cdot \frac{Q'}{Q^*}, \tag{1}$$

where R_a is the surface roughness function.

The surface roughness function is modeled experimentally on external cylindrical grinding with T1 tool steel as by the eq. (2):

$$R_a \leq R_a^*, \tag{2}$$

R_a^* is the limit of surface roughness. That is the value of surface roughness when replacing the upper boundary condition of the variables into the mathematical function of surface roughness.

Q' is the material removal rate function. Q' is determined by the eq. (3):

$$Q' \geq Q^*, \tag{3}$$

where Q^* is the limit value of the material removal rate criteria.

2. 1. 3. The Constraints

Functional constraints. The constraints on cutting force and vibration functions are determined by the eq. (4) to the eq. (6):

$$F_y = f(S_d, t, HRC) \leq F_y^*, \tag{4}$$

$$F_z = f(S_d, t, HRC) \leq F_z^*, \tag{5}$$

$$A = f(S_d, n_w, t) \leq A^*. \tag{6}$$

Variable constraints [12]. The variable constraints are determined by the eq. (7) to the eq. (10). Feed rate:

$$S_d^{\min} \leq S_d \leq S_d^{\max}. \tag{7}$$

Workpiece speed:

$$n_w^{\min} \leq n_w \leq n_w^{\max}. \tag{8}$$

Cutting depth:

$$t_{\min} \leq t \leq t_{\max}. \tag{9}$$

Hardness of workpiece material:

$$HRC_{\min} \leq HRC \leq HRC_{\max}, \tag{10}$$

where:
  – S_d – Axial Feed rate (mm/rev);
  – n_w – Rotation speed of workpiece (rpm);
  – t – Cutting depth (mm);
  – HRC – Rockwell hardness of workpiece;
  – F_y – Amplitude of cutting force along the Oy (N);
  – F_z – Amplitude of cutting force along the Oz (N);
  – A – Acceleration amplitude (m/s^2);
  – F_y^*, F_z^*, A^* are the boundary limits of the normal force, tangential force and vibration amplitude, respectively, which are determined by the strength, firmness of the machine, and the cutting tool.

2. 1. 4. The Weights
Weights of surface roughness and machining productivity are w_1 and w_2. These values that are in the range (0, 1), allow to determine the corresponding effects of R_a and Q'. The sum of these coefficients is 1 as by the eq. (11) [13].

$$w_1 + w_2 = 1. \tag{11}$$

If the priority of the variables is not the same, the variable with a larger coefficient will be more important. Depending on the purpose of the grinding process, if it is a rough grinding process, the productivity will be an important goal, the coefficient w_2 will be larger. On the contrary, if it is a finish grinding process, the surface roughness is an important goal, so the coefficient w_1 will be larger.

2. 2. Experimental setup
2. 2. 1. Experimental machine
The external cylindrical grinding machine MEG-120 MAGNUM CUT was used to perform the experiments as illustrated in **Fig. 2**.

Fig. 2. External cylindrical grinding machine MEG-112

The rotation speed of grinding wheel is 2000 rpm, the rotation speed of workpiece is 650 rpm, the movement speed of the stepless machine table is from 0.1 to 5 meters per minute (mm/rev).

2. 2. 2. Workpiece and grinding wheel

The experimental workpieces with the diameter of 40 mm was used in grinding process as described in **Fig. 3**. The workpiece material is T1 tool steel that was heat treated to achieve the hardness of 40, 50, and 60 HRC. The composites of T1 tool steel was listed in **Table 1**.
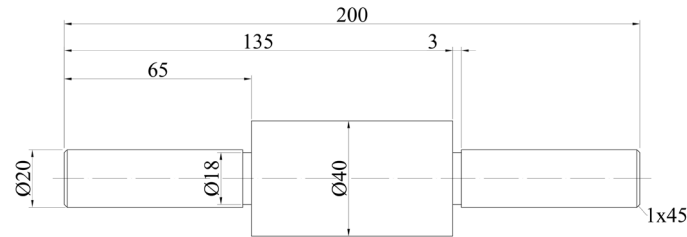

Fig. 3. Workpiece dimensions

Table 1

The components of T1 tool steel

Steel brand	Chemical composition (%)
ASTM: T1 tool steel	C 0.7–0.8, Si ≤ 0,4, Mn ≤ 0.4, Cr 3.8–4.4, V 1–1.4, W 17.5–19

The experimental grinding wheel has the size 400×50×203, 3-grain diamond stone dressing tool with size: 8.5×40 using the grinding method with the center of the feed rate.

2. 2. 3. Measurement system

MITUTOYO-SJ-400 Surface Roughness Tester (Japan) was used to measure the surface roughness of the workpiece as illustrated in **Fig. 4**. The cut-off length and evaluation length were fixed at 0.8 mm and 4 mm, respectively. The surface roughness was measured parallel to the machined surface repeated three times following three repeated times of each cutting test. The average values of the measurements were evaluated.

The setting of cutting forces measurement is illustrated in **Fig. 5**.

Fig. 4. The surface roughness tester Mitutoyo Surflest SJ-400
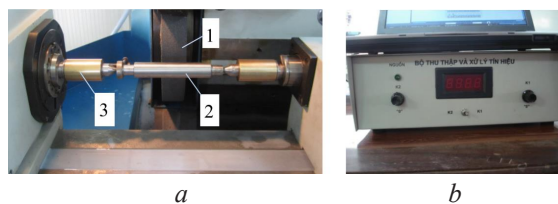

a   *b*

Fig. 5. The setting of cutting force measurement: *a* – Grinding wheel (1), workpiece (2) and Force sensor (3); *b* – Signal processing system

The vibration measurement system that included the acceleration sensor Triaxial DeltaTron Accelerometer with TEDS Type 4525-B-001, the stored data LAN-XI, and the PULSE FFT 7770 module was used to measure the machine-tool vibrations. The detail is illustrated in **Fig. 6 [**14**]**.

All the measuring devices are connected simultaneously to ensure the system synchronization.

| a | b | c |
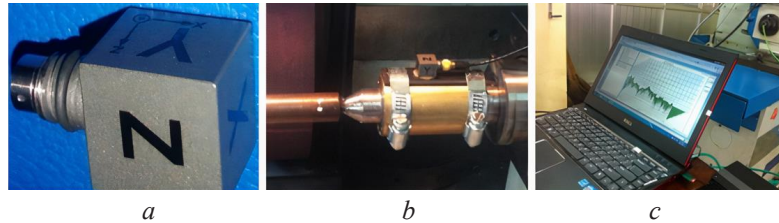
Fig. 6. Setting of vibration measurement:
a – Vibration sensor*; b* – Measurement position*; c* – Data processing system

2. 2. 4. Design of the experimental matrix

From the trial grinding tests, the effect of the grinding conditions and workpiece hardness on the surface roughness, the cutting forces, and the vibrations were determined. The important factors that influence on the surface roughness are the axial feed rate, the workpiece speed, the cutting depth, and the workpiece hardness. There are three important factors (axial feed rate, cutting depth, and workpiece hardness) that influence on the cutting forces. And there are three important factors (axial feed rate, workpiece speed, and cutting depth) that influence on the vibration. So, the levels of experimental factors and the experiment design of this study were listed from **Tables 2**–**7**.

Table 2
Machining parameters and their levels in surface roughness measurement

Factors	Unit	Levels		
		Level 1 (–1)	Level 1 (0)	Level 1(1)
Axial feed rate S_d	mm/rev	0.3	0.4	0.5
Workpiece speed n_w	rpm	100	150	200
Cutting depth t	mm	0.005	0.015	0.025
Workpiece hardness	HRC	40	50	60

Table 3
Experimental matrix and measured results of surface roughness

No.	Input factors								R_a (µm)
	Coded factors				Machining parameters				
	X_1	X_2	X_3	X_4	S_d (mm/rev)	n_w (rpm)	t (mm)	HRC	
1	–1	–1	–1	–1	0.3	100	0.005	40	0.32
2	+1	–1	–1	–1	0.5	100	0.005	40	0.35
3	–1	+1	–1	–1	0.3	200	0.005	40	0.37
4	+1	+1	–1	–1	0.5	200	0.005	40	0.41
5	–1	–1	+1	–1	0.3	100	0.025	40	0.56
6	+1	-1	+1	–1	0.5	100	0.025	40	0.6
7	–1	+1	+1	–1	0.3	200	0.025	40	0.66
8	+1	+1	+1	–1	0.5	200	0.025	40	0.69
9	–1	–1	–1	+1	0.3	100	0.005	60	0.28
10	+1	–1	–1	+1	0.5	100	0.005	60	0.31
11	–1	+1	–1	+1	0.3	200	0.005	60	0.34
12	+1	+1	–1	+1	0.5	200	0.005	60	0.37
13	–1	–1	+1	+1	0.3	100	0.025	60	0.56
14	+1	–1	+1	+1	0.5	100	0.025	60	0.59
15	–1	+1	+1	+1	0.3	200	0.025	60	0.62
16	+1	+1	+1	+1	0.5	200	0.025	60	0.68

Table 4

Machining parameters and their levels in cutting force measurement

Factors	Unit	Levels		
		Level 1 (–1)	Level 2 (0)	Level 3 (1)
Axial feed rate S_d	mm/rev	0.3	0.4	0.5
Cutting depth t	mm	0.005	0.015	0.025
Workpiece hardness	HRC	40	50	60

Table 5

Experimental matrix and measured results of cutting forces

No.	Input factors						Performance measures	
	Coded factors			Machining parameters				
	X_1	X_2	X_3	S_d (mm/rev)	t (mm)	HRC	F_y (N)	F_z (N)
1	–1	–1	–1	0.3	0.005	40	7.10	3.45
2	+1	–1	–1	0.5	0.005	40	12.33	4.24
3	–1	+1	–1	0.3	0.025	40	12.85	5.15
4	+1	+1	–1	0.5	0.025	40	25.43	9.33
5	–1	–1	+1	0.3	0.005	60	16.55	6.23
6	+1	–1	+1	0.5	0.005	60	20.64	7.78
7	–1	+1	+1	0.3	0.025	60	19.36	7.45
8	+1	+1	+1	0.5	0.025	60	30.32	14.21

Table 6

Machining parameters and their levels in vibration measurement

Factors	Unit	Levels		
		Level 1 (–1)	Level 2 (0)	Level 3 (1)
Axial feed rate S_d	mm/rev	0.3	0.4	0.5
Workpiece speed n_w	rpm	100	150	200
Cutting depth t	mm	0.005	0.015	0.025

Table 7

Experimental matrix and measured results of vibration

No.	Input factors						A (m/s^2)
	Coded factors			Machining parameters			
	X_1	X_2	X_3	S_d (mm/rev)	n_w (rpm)	t (mm)	
1	–1	–1	–1	0.3	100	0.005	0.766
2	+1	–1	–1	0.5	100	0.005	0.888
3	–1	+1	–1	0.3	200	0.005	0.913
4	+1	+1	–1	0.5	200	0.005	0.998
5	–1	–1	+1	0.3	100	0.025	0.933
6	+1	–1	+1	0.5	100	0.025	1.237
7	–1	+1	+1	0.3	200	0.025	1.108
8	+1	+1	+1	0.5	200	0.025	1.319

The **Tables 2**–**7** above show the measured values of roughness, cutting force and vibration at different test levels.

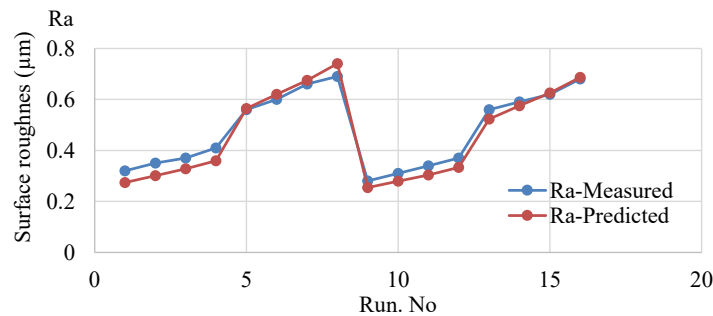**3. Results**
    3. 1. The regression and verification of experimental models
    3. 1. 1. Regression of surface roughness model
    The experimental results were stored as in **Table 3** for the surface roughness, **Table 5** for the cutting forces, and **Table 7** for the vibration. By analyzing of the experimental data, the surface roughness in the grinding process was modeled as the exponential function (12). The verification results of surface roughness model were described in **Fig. 7**. As seen from this figure, the predicted results were quite close to the experimental results. There is a quite good relation between predicted values and test values. The surface roughness models can be used to optimize the grinding parameters of the grinding process.

Fig. 7. Measured and predicted results of surface roughness

The surface roughness model in exponential function:

$$R_a = 2.2463 S_d^{0.1559} n_w^{0.2204} t^{0.4277} HRC^{-0.1605}. \tag{12}$$

    To assess the appropriateness of the regression equation is to check whether the model obtained correctly describes our experiments or not. Let's use Fisher standard to compare:

$$F_{cal} < F_{tab}(P, k_1, k_2), \tag{13}$$

in which $k_1 = N - n - 1$; $k_2 = N(m-1)$; N – number of experiments ($N=8$); n – number of factors affecting the test results ($n=3$); m – number of repetitions of the experiment ($m=3$). So: $k_1 = 4$; $k_2 = 16$:

$$F_{cal} = \frac{S_c^2}{S_r^2}. \tag{14}$$

Compatible variance:

$$S_c^2 = \frac{m}{N-n-1} \sum_{i=1}^{N} (\bar{y}_i - \hat{y}_{tb})^2. \tag{15}$$

Repetitive variance:

$$S_r^2 = \frac{1}{N} \sum_{i=1}^{n} S_i^2 = \frac{1}{N(m-1)} \sum_{i=1}^{N} \sum_{j=1}^{m} (y_{ij} - \bar{y}_i)^2, \tag{16}$$

where $\hat{y}_i$ – experimental results No. i calculated according to the regression equation; $\bar{y}_i$ – the average value of m times experiments in the ith experiment; y_{ij} – the value of the ith experiment in the jth iteration; $\bar{y}_i - \hat{y}_i$ – error between theory and experiment in ith experiment.
    Basing on experimental results according to the regression eq. (12), the evaluation values of the surface roughness regression model (R_a) were calculated as following:

$$S_c^2 = 0.1981; \quad S_r^2 = 0.1102.$$

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According to the Fisher standard [15]:

$$F_{cal}=1.797<F_{tab}(11,32,0.95)=2.1.$$

Thus, eq. (12) is consistent with reality.

3. 1. 2. Regression of cutting force models

By the same way, the cutting forces in the grinding process were modeled as the exponential functions (17), (18). The verification results of cutting force models were described in. As seen from **Fig. 8, 9**, the predicted results were quite close to the experimental results. The cutting force models can be used to optimize the grinding parameters of the grinding process.
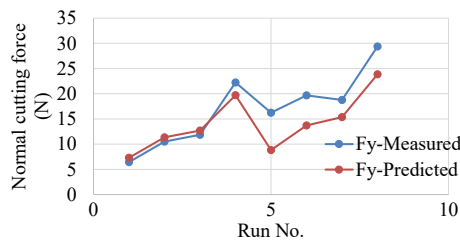
Fig. 8. Measured and predicted results of normal cutting force
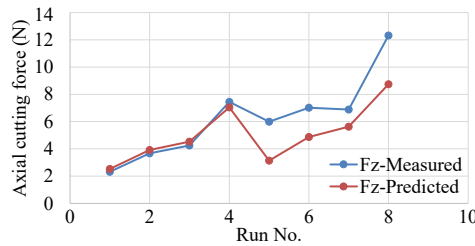
Fig. 9. Measured and predicted results of axial cutting force

The normal cutting force model in exponential function:

$$F_y = 36.445 S_d^{0.9324} t^{0.3507} HRC^{0.3373}. \tag{17}$$

The axial cutting force model in exponential function:

$$F_z = 13.397 S_d^{0.8176} t^{0.3655} HRC^{0.3662}. \tag{18}$$

Basing on experimental results according to the regression (17), the evaluation values of the cutting force regression model (F_y) were calculated as following:

$$S_c^2 = 0.0623; S_r^2 = 0.0534.$$

According to the Fisher standard [14]:

$$F_{cal}=1.17<F_{tab}(4,16,0.95)=3.0.$$

Basing on experimental results according to the regression (18), the evaluation values of the cutting force regression model (F_z) were calculated as following:

$$S_c^2 = 0.0599; \quad S_r^2 = 0.0532.$$

So, $F_{cal}=1.13<F_{tab}(4,16,0.95)=3.0$. Thus, eq. (17), (18) are consistent with reality.

3. 1. 3. Regression of vibration model

By the same way, the vibration in the grinding process was modeled as the exponential function (19). The verification results of surface roughness model were described in **Fig. 10**. As seen from this figure, the predicted results were quite close to the experimental results. The vibration models can be used to optimize the grinding parameters of the grinding process.
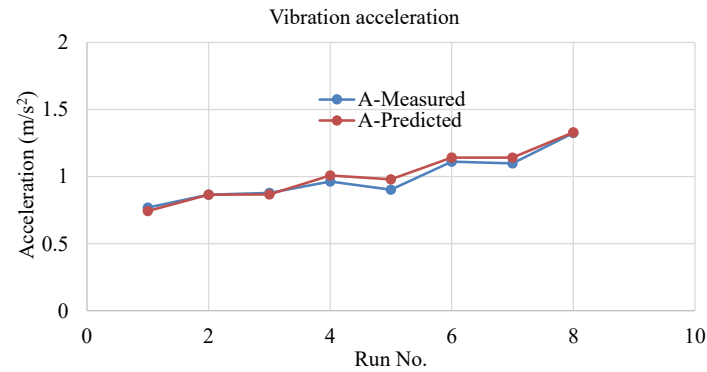

Fig. 10. Measured and predicted results of amplitude vibration

The amplitude vibration model in exponential function:

$$A = 1.2409 S_d^{0.3397} n_w^{0.1908} HRC^{0.1809}. \tag{19}$$

Basing on experimental results according to the regression eq. (19), the evaluation values of the vibration regression model (A) were calculated as following:

$$S_c^2 = 0.0139; \quad S_r^2 = 0.0135.$$

According to the Fisher standard [14]:

$$F_{cal} = 1.03 < F_{tab}(4, 16, 0.95) = 3.0.$$

Thus, eq. (19) is consistent with reality.

3. 2. Multi-Objective optimization of Cutting Conditions in Grinding process
3. 2. 1. The Objective functions

The surface roughness function. The surface roughness function is constructed experimentally on external cylindrical grinding as by the eq. (12). Is the value when replacing the upper boundary condition of the variables into the mathematical functions as above. In this study $R_a^* = 0.69 \, \mu m$.

The material removal rate function. The material removal rate in grinding process was calculated by the eq. (20) to the eq. (23):

$$Q = v_w \cdot t \cdot b_s, \tag{20}$$

t is the cutting depth, mm; b_s is the width of the grinding wheel. Due to the constant width of the grinding wheel, the material removal rate function can be calculated as by the eq. (21):

$$Q' = v_w \cdot t. \tag{21}$$

Workpiece speed v_w is calculated according to the eq. (22).

$$v_w = \frac{\pi d_w n_w}{60}. \tag{22}$$

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So,

$$Q' = \frac{\pi d_w n_w t}{60},$$ (23)

where d_w is the diameter of the workpiece; n_w is the number of revolutions of the workpiece.

Condition $Q' \geq Q^*$. In this case, $Q^* = 0.523$ mm²/s.

3. 2. 2. The constraints

Functional constraints. The function constraints on cutting force and vibration functions are determined by the eq. (24) to the eq. (29):

$$F_y = f(S_d, t, HRC) \leq F_y^* = 100 \text{ N},$$ (24)

$$F_z = f(S_d, t, HRC) \leq F_z^* = 50 \text{ N},$$ (25)

$$A = f(S_d, n_w, t) \leq A^* = 2 \text{ m/s}^2.$$ (26)

Variable constraints [9]. The variable constraints on cutting conditions and workpiece hardness are determined by the eq. (27) to the eq. (30). Feed rate:

$$0.3 \leq S_d \leq 0.5 \text{ (mm/rev)}.$$ (27)

Rotation speed of workpiece:

$$100 \leq n_w \leq 200 \text{ (rpm)}.$$ (28)

Cutting depth:

$$0.0025 \leq t \leq 0.025 \text{ (mm)}.$$ (29)

Hardness of machining materials:

$$40 \leq HRC \leq 60.$$ (30)

The program is programmed directly on MATLAB software. Running the program with the module Optimization Tool/Multi objective optimization using Genetic Algorithm for grinding process of T1 tool steel.

3. 2. 3. Weight

In this study, considering the priority of the variables to be the same, the coefficient w_1 equal the coefficient w_2. Then the multi-objective function can be expressed as by the eq. (31):

$$M = 0.5\frac{R_a}{R_a^*} - 0.5\frac{Q'}{Q^*}.$$ (31)

In case to prioritize a goal, it is possible to choose a greater weight but still have to ensure that the sum of the weights is 1.

3. 2. 4. The optimization results

The optimization results were stored in **Tables 8, 9**. The Genetic Algorithm graphs were described in **Fig. 11**. The results of the program show the stability of the variable values. Although the values changed, the range is very small. Hence, the average values were employed in the run lead to a fast convergence speed. However, the rapid convergence rate is also the disadvantage of the

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algorithm. If the convergence is too fast, the reliable information growing in the population will be overlooked and lead to a locally optimal solution. To overcome this disadvantage, let's first select the number of generations for the first run and then increase in the number of generations until the graph are always a straight line that is to achieve the global optimal value.

Results with 5 running times show that the optimal value for each run is variable but the difference is not so much. The average value of the runs can be used to predict the values of surface roughness and the material removal rate **Fig. 11**.

Table 8

Results of the program run with T1 tool steel

Variable	S_d (mm/rev)	n_w (rpm)	t (mm)	HRC
1st run	0.3	187.25	0.015	54.5
2nd run	0.3	189.16	0.014	54.3
3th run	0.3	187.01	0.015	55.2
4th run	0.3	193.10	0.014	54.7
5th run	0.3	183.76	0.016	55.2

Table 9

Results of running the program, taking the average values after 5 runs

Parameters	S_d (mm/rev)	n_w (rpm)	t (mm)	HRC	R_a (µm)	F_y (N)	F_z (N)	A (m/s²)	Q' (mm²/s)
Optimized values	0.3	188.1	0.015	54.78	0.51	10.441	4.648	1.045	5.906
Constraint values	0.3÷0.5	100÷200	0.0025÷0.025	40÷60	Min	100	50	2	Max
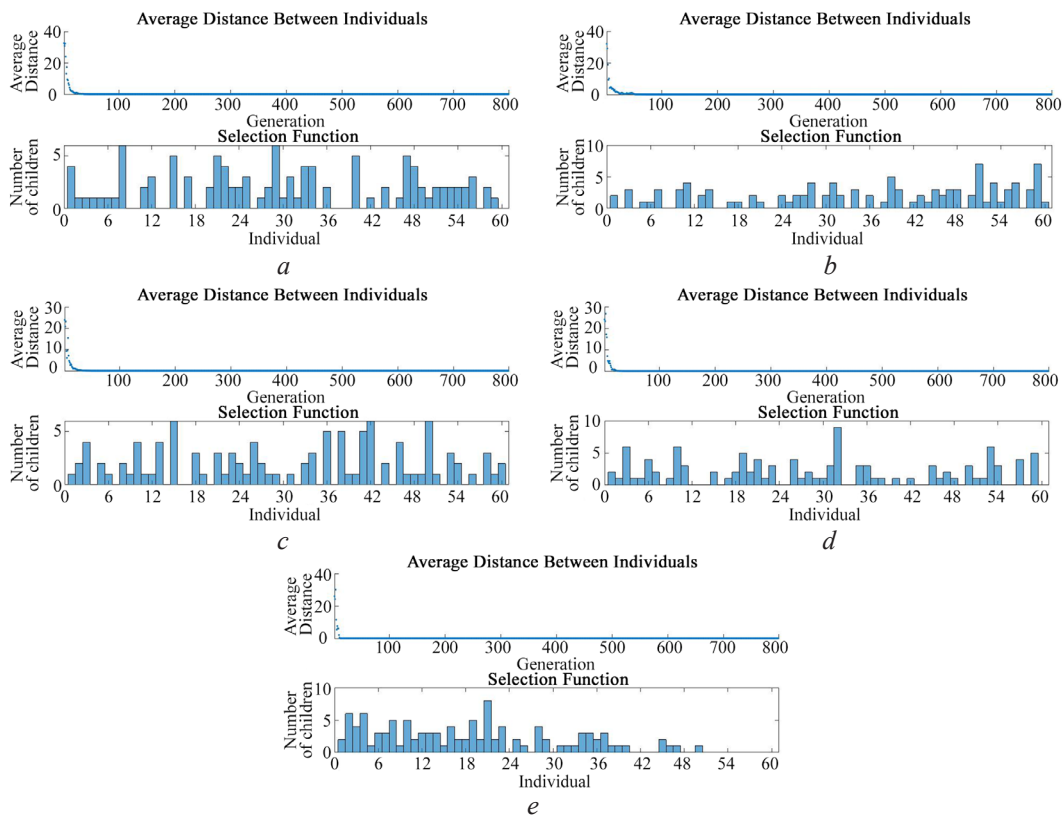
Fig. 11. Genetic algorithm graph for grinding T1 tool steel: *a* – Time 1; *b* – Time 2; *c* – Time 3; *d* – Time 4; *e* – Time 5

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From the adaptive function, there is many optimization options by changing the coefficients w_1, w_2 depending on which priority for the target. For example, in a roughing process, it is necessary to prioritize productivity targets by choosing a large w_2 coefficient. Or when finishing requires a priority to achieve the target is the surface roughness let's choose a large w_1 coefficient. When w_1 or w_2 is zero, the problem becomes a single-objective problem.

3. 3. Experimental using the optimal values

Using the optimal values of the cutting parameters and the hardness of the workpiece, the verification experiments were conducted. The comparison results of experimental and predicted values of surface roughness, cutting force amplitude, vibration amplitude, and material removal rate are calculated and listed in **Table 10**.

Table 10
The predicted and experimental results with optimal parameters

Parameters	R_a (mm)	F_y (N)	F_z (N)	A (m/s²)	Q' (mm²/s)
Experimental	0.530	10.972	4.531	1.135	5.466
Predicted	0.510	10.441	4.648	1.045	5.906
Error (%)	3.8	1.8	6.5	7.9	7.5

In **Table 10**, the maximum error is the error of vibration with 7.9 %. Minimum error is the error of normal cutting force with 1.8 %.

4. Discussions of experimental results

From mathematical models (12), (17)–(19) showed that surface roughness when external cylindrical grinding of T1 tool steel is proportional to cutting parameters but inversely proportional to machining material hardness. They also show that both the cutting force F_y and F_z are directly proportional to the cutting parameters and the hardness of the workpiece. In which, the normal cutting force F_y is much greater than the tangential cutting force F_z. The large F_y cutting force is due to the loss of energy to separate the chip from the part when there is the penetration of the grinding grain, the higher the hardness of the material, the more difficult the grinding ability of the grinding grain. In addition, vibration during outer circular grinding is also proportional to the cutting parameters.

The results from **Table 10** showed that the prediction of surface roughness, cutting force amplitude, vibration amplitude, and material removal rate were very close to the experimental results. The maximum difference between predicted and experimental values was 7.9 % (for vibration amplitude). So, the combination of GAs and weighting method that was proposed in this study can be applied to improve the productivity and reduce the surface roughness of the workpiece in external cylindrical grinding process using T1 tool steel.

Because grinding is the process of cutting materials including cutting, scratching and rubbing with abrasive particles at very high speeds, so the heat generated during the grinding process is quite large. However, in this study, the thermal model has not been built up during the grinding process, nor has the effect of heat on the surface roughness and machining productivity be evaluated when external cylindrical grinding. This is a difficult problem to do because the coolant must be used during the external cylindrical grinding process, so the use of existing thermometers will give inaccurate results. The solution is being researched and resolved in the future by us.

5. Conclusion

In this study, an experimental method was performed to model the surface roughness, cutting forces, and vibration, and to optimize the cutting parameters in the external cylindrical grinding process of the T1 tool steel. Depending on the analysis of experimental results, the conclusions of this study can be drawn as follows.

In the external cylindrical grinding process, the surface roughness, cutting force amplitude, and vibration amplitude were modeled as the exponential functions of cutting parameters (axial

feed rate, workpiece speed, and cutting depth) and the workpiece hardness. These models were successfully verified by experimental results with very promising results.

A combination of GAs and weighting method was successfully applied to solve the multi-objective optimization problem. Using this proposed combination method, the productivity and surface roughness quality were improved.

The optimum values of input parameters were a feed rate of 0.3 mm/rev, a workpiece speed of 188.1 rpm, a cutting depth of 0.015 mm, and a workpiece hardness of 54.78 HRC. Using these optimal values, the surface roughness and material removal rate were obtained to be 0.510 μm and 5.906 mm^2/s, respectively. The optimal values were successfully verified by experimental results with very promising results. The maximum difference between predicted and experimental values was 7.9 %.

The proposed method of this study can be applied in industrial machining to improve the productivity and quality of the products in external cylindrical grinding process of the T1 tool steel, and can be extended to the other machining processes such as milling, turning, drilling, etc. and another workpiece, tool materials. These are the future studies.

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