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Optimization of Cutting Parameters for Sustainable Machining of Titanium Ti-5553 Alloy using Genetic Algorithm

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Abstract

Titanium Ti-5553 alloys have been considered as difficult-to-machine materials due to the extremely high tool wear, high cutting forces, high temperature, and poor surface quality of machined parts. Process parameters needs to be optimized in order to improve machining performance and in the meantime reducing manufacturing cost. This study proposes sustainable machining process for this new generation Titanium Ti-5553 alloy. Process parameters including depth of cut, cutting speed, and feed rate were taken into account to optimize parameters better tool life, material removal rate and surface roughness together with energy consumption for the first time in literature. Genetic algorithm was utilized for optimizing the process parameters. Obtained results illustrated that optimization using genetic algorithm is a very effective approach to substantially improve machining performance of this alloy and make machining process of this alloy more sustainable by reducing energy consumption, manufacturing cost and increasing material removal rate in machining process of new generation titanium alloy.

Keywords: Ti-5553 Alloy, Optimization, Genetic Algorithm, Machining Performance

1. INTRODUCTION

Titanium alloys are widely used in the aerospace industry, the chemical industry and medical engineering [1] because of their higher yield strength, excellent fatigue crack growth resistance and good hardenability [2]. Among Titanium alloys, Ti-5553 (Ti–5Al–5Mo–5V–3Cr) is a recently developed near beta Ti alloy that is gathering increasing interest in aircraft structural applications, especially in the landing gear components [2]. While this alloy gains interest due to its superior properties, it is categorized as difficult-to-machine materials due to its low thermal conductivity, low modulus of elasticity, high strength at elevated temperature, etc. Therefore, machining processes of this alloy needs also special attention, consequently it would be possible to control the processing of this alloy. During machining process of this alloy both the part quality and machining performance and cost of machining processes needs to be taken into account. This can be achieved by considering the basic elements of sustainable machining that includes machining cost, power consumption, waste management, personal health, environmental friendliness, etc [3].

Although the ideal approach should consider all basic elements to provide sustainable machining operation for this difficult-to-machine alloy, it may not be possible to take all elements into account. In the meantime, optimizing the process allow us to consider more than one element in one operation. By implementing optimization approach in this study, it is aimed to control energy consumption, machining cost and part quality by focusing on cutting forces, material removal rate, tool life, and surface quality of machined work materials. These outputs are the main concern as studies indicate that most of the environmental impacts related to machine tools are due to their energy consumption [4]. The selection of optimal parameters has great effect on achieving reduction in machining cost. Referring to this machining process, several works have been published regarding the optimization of the cutting parameters; many of them employed the surface roughness, cutting force, cutting power, tool life and material removal rate as optimization criteria [5]. Despite decades of optimizing of machining operations based on cost and productivity, optimizing energy consumption had not received significant attention [6]. Most of the researchers in the area of machining have used various techniques for finding the optimal machining parameters for single- and multi-pass turning operations [7].

In literature, various optimization techniques have been used to find optimum machining conditions including artificial neural network [8] and fuzzy set theory-based modelling techniques, statistical regression approach, and conventional optimization [9] techniques including Taguchi, Response Surface Design Methodology, iterative

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mathematical search technique, and non-conventional techniques such as heuristic search techniques. Genetic algorithm (GA), etc [10]. The Genetic Algorithm (GA) is inspired by the genetic process of biological organisms. GA have been demonstrated to converge to the optimal solution for many diverse difficult problems, although optimality cannot be guaranteed [11]. GAs have been shown in practice to be very effective at function optimization; efficiently searching large and complex (multimodal, discontinuous, etc.) spaces, to find nearly global optima [8]. Researchers claimed that GA have significant superiority over other optimization techniques for solving the non-linear optimization problems in machining parameters optimization [12]. Researchers used GA to achieve optimum machining parameters for considered objective which are material removal rate, surface roughness, minimum unit production cost, [7] production time, tool life and cutting power [13].

In this study, to find optimum machining parameters to increase surface quality, material removal rate and tool life together with considering energy consumption, Genetic Algorithm have been proposed. Our study indicates that utilizing this technique has very high potential to contribute to make machining process of this new generation titanium alloy more sustainable.

2. METHODOLOGY

2.1. Empirical Model

Cutting parameters such as cutting speed, feed rate and depth of cut are considered for empirical models due to their significant effect on cutting force, surface roughness and flank wear in turning operation. The relationship between cutting force, surface roughness, flank wear and decision variables can be defined as follows [14]:

$$F_c = C_1 {V_c}^{a_1} f^{b_1} {a_p}^{c_1} \quad (1)$$
$$R_a = C_3 {V_c}^{a_3} f^{b_3} {a_p}^{c_3} \quad (2)$$
$$V_B = C_3 {V_c}^{a_3} f^{b_3} {a_p}^{c_3} \quad (3)$$

Where F_c, R_a, V_B, V_c, f and a_p are cutting force, surface roughness, flank wear, cutting speed, feed rate and depth of cut, also a_i, b_i, c_i and C_i are empirical constants. Forms of polynomials which can be approved to represent cutting force, surface roughness and flank wear in turning are the first order models:

$$lnF_c = lnC_1 + a_1 lnV_c + b_1 lnf + c_1 lna_p \quad (4)$$
$$lnR_a = lnC_2 + a_2 lnV_c + b_2 lnf + c_2 lna_p \quad (5)$$
$$lnV_B = lnC_3 + a_3 lnV_c + b_3 lnf + c_3 lna_p \quad (6)$$

and second order models can be described as:

$$\omega_1 = \omega - \varepsilon_1 = k_0 + k_1x_1 + k_2x_2 + k_3x_3 + k_{1_2}x_1x_2 + k_{1_3}x_1x_3 + k_{2_3}x_2x_3 + k_{1_1}{x_1}^2 + k_{2_2}{x_2}^2 + k_{3_3}{x_3}^2 \quad (7)$$

$$\varphi_1 = \varphi - \varepsilon_2 = l_0 + l_1x_1 + l_2x_2 + l_3x_3 + l_{1_2}x_1x_2 + l_{1_3}x_1x_3 + l_{2_3}x_2x_3 + l_{1_1}{x_1}^2 + l_{2_2}{x_2}^2 + l_{3_3}{x_3}^2 \quad (8)$$

$$\gamma_1 = \gamma - \varepsilon_3 = m_0 + m_1x_1 + m_2x_2 + m_3x_3 + m_{1_2}x_1x_2 + m_{1_3}x_1x_3 + m_{2_3}x_2x_3 + m_{1_1}{x_1}^2 + m_{2_2}{x_2}^2 + m_{3_3}{x_3}^2 \quad (9)$$

Where ω, φ, γ, x_1, x_2, x_3, k, l and m are logarithmic transformation of cutting force, surface roughness, flank wear, cutting speed, feed rate, depth of cut and empirical constants, ε is the experimental error and ω_1, φ_1 and γ_1 are estimated cutting force, surface roughness and flank wear.

2.2. Multi-Objective Optimization

Multi-Objective problems usually have more than one solution known as pareto-optimal solution [15, 16]. Evolutionary multi-objective optimization (EMO) methods aim to gain [17] non-dominated points, when shown in a diagram, named as Pareto Front [18]. The general multi-objective optimization problem is conceived as follow:
Minimize or maximize:

$$f(x) = [f_1(x), f_2(x), \ldots, f_\alpha(x)]^\beta \quad (10)$$

subject to:

$$g_i(x) < 0 \qquad i = 1, 2, ..., k$$
$$h_j(x) = 0 \qquad j = 1, 2, ..., l$$

Where α is the count of objective function, k is the count of disequilibrium constraints and l is the count of equilibrium constraints [19]. A multi-objective problem with α objectives is described as given a z-dimensional decision variable vector $\mathbf{x=\{x_1,x_2,\ldots x_z\}}$ in the solution area X, determine a vector X* that minimize or maximize given set of α objective functions $\mathbf{M(x^*)=\{M_1(x^*),M_2(x^*),\ldots,M_a(x^*)\}}$ [20]. A solution **x** is called as non-dominated if there is no $\mathbf{x}^{l}$ such that $\mathbf{f(x^{l})<f(x)}$ for minimization and $\mathbf{f(x^{l})<f(x)}$ for maximization. The illustration of this non-dominated solutions that known as Pareto optimal set, is the Pareto front if there are two or three objectives [21].

2.3. Genetic Algorithm

All application of genetic algorithm start with procure an initial population that was created randomly and go forward with calculate fitness of each individual [22]. Then it select individuals which pass next generation and parents which are needed for generating other members of next population by crossover operator which combine relevant feature of parent solutions [23] and mutation operator which is the process of random alteration at generated individuals with small probability [24]. The algorithm stops when any stopping criterion is provided [25]. Previous studies already confirmed that this algorithm is very efficient to optimize parameters in machining operations. Thus, this study also uses this algorithm for optimization.

3. APPLICATION IN TURNING

The workpiece used in this work was Ti-5553 bar with a diameter of 20 mm, which was hot rolled. The cutting tests were conducted on a Doosan CNC turning center at dry condition. Uncoated 883 grade carbide inserts were used with ISO designation CNMG120408 M1 that is suitable for machining of titanium alloys. PTJNL2525M16 tool holder with the rake angle of α= -6 degree was used. During machining trials, three different feed rates, *f*, five different cutting speeds, V_c, and three different depth of cut, a_p, were used that are presented in Table 1. Experimental setup is presented in Fig.1. The detail of measurements of outputs used in this study is presented in elsewhere [26].

The variation of experimentally measured flank wear with respects to cutting speed and the variation of surface roughness resulting from various feed rates are presented in Fig.2. Empirical model was developed to predict these experimental data using multiple-nonlinear regression analysis.

Table 1. Machining parameters and their levels

Cutting condition	Cutting speed, V_c (m/min)	Depth of cut, a_p (mm)	Feed rate, f (mm/rev)
Dry	40	0.8	0.1
	80	1.4	0.15
	120	2	0.2
	160		
	200		

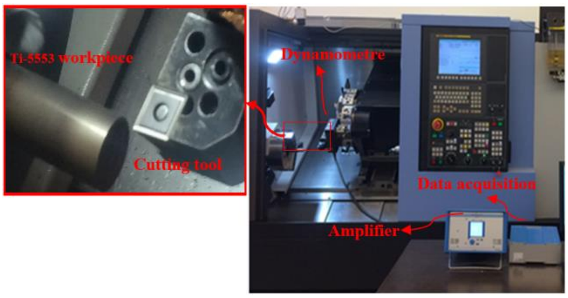

Figure 1. Experimental setup.

The correlations between cutting parameters including depth of cut, cutting speed and feed rates and measured outputs were achieved by multiple non-linear regression. These regression models are presented in equations 11, 12, and 13 as shown. Fig. 2 shows the agreement between experimentally measured data and results obtained from multiple non-linear regression for the outputs of flank wear and surface roughness.

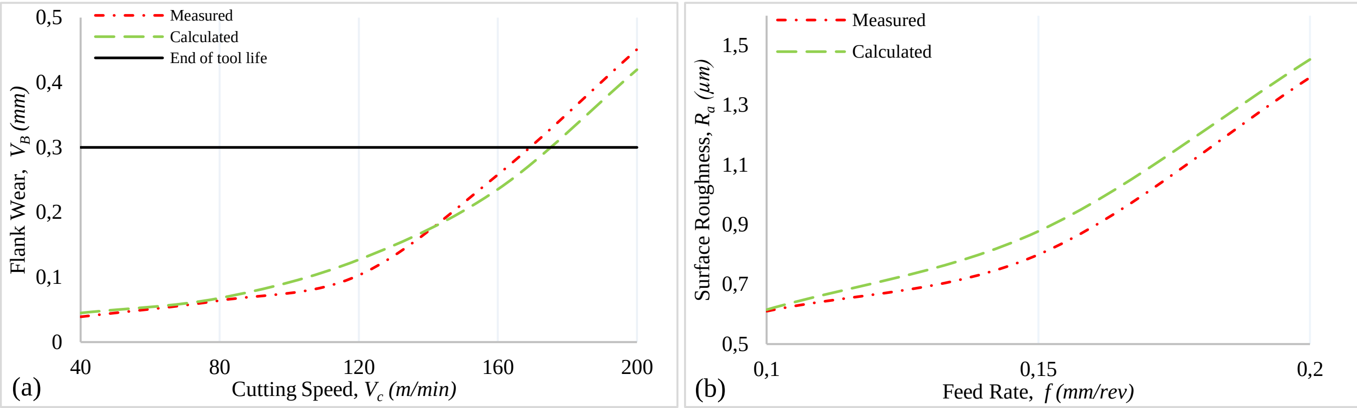

Figure 2. (a) Flank wear at various cutting speeds; (b) surface roughness at various feed rates.

$$\omega_1 = 6.637 + 0.29x_2 - 0.806x_3 - 0.053x_1x_2 + 0.361x_1x_3 - 0.04x_2x_3 - 0.003{x_1}^2 - 0.162{x_2}^2 + 0.328{x_3}^2 \quad (11)$$

$$\varphi_1 = 5.682 + 0.538x_1 + 5.943x_2 - 0.305x_3 + 0.035x_1x_2 - 0.058x_1x_3 - 0.328x_2x_3 - 0.058{x_1}^2 + 1.264{x_2}^2 + 0.144{x_3}^2 \quad (12)$$

$$\gamma_1 = 8.483 - 7.137x_1 - 2.295x_2 - 1.833x_3 - 0.415x_1x_2 + 0.948x_1x_3 + 0.75x_2x_3 + 0.865{x_1}^2 - 1.104{x_2}^2 - 0.269{x_3}^2 \quad (13)$$

It is obvious that the model is capable of well predicting the data obtained by experimental work. The R square statistics are equal to 0.9896 for cutting force, 0.8512 for surface roughness and 0.8163 for flank wear.

4. RESULT AND DISCUSSIONS

4.1. Minimizing Flank Wear and Maximizing Material Removal Rate

Considering the cost of cutting tools used in machining, it can be considered as a significant contribution if tool life can be increased by controlling tool wear. Besides, in mass production, the manufacturing time directly influence the cost of production. Therefore, it is always desired to decrease the machining time by increasing material removal rate. Thus, we aim to optimize cutting parameters by using multi-objective optimization approach to minimize flank wear and maximize material removal rate when maximum surface roughness is kept as 0.8 µm in this part of study. The constraint of flank wear is 0.3 mm that is equal to tool life according to ISO 3685:1993 [27, 28]. The unit of material removal rate is taken as mm^3/min in the following well-known equation.

$$MRR = 1000 V_c f a_p \quad (14)$$

Minimize:	V_B
Maximize:	MRR
Subject to:	$R_a < 0.8$ mm
	$V_B < 0.3$ µm
	40 m/min $< V_c <$ 200 m/min
	0.1 mm/rev $< f <$ 0.2 mm/rev
	0.8 mm $< a_p <$ 2 mm

The obtained result is represented in Fig. 3. Constraint of surface roughness prevents to increase cutting parameters for all non-dominated solutions. The maximum material removal rate is obtained as 20658 mm^3/min when flank wear reaches the upper limit, that consequently the end of the tool life. While flank wear at the lowest value, the most desirable value occur for maximum tool life that designated by the value of flank wear. While material removal rate at lowest as 6592 mm^3/min, the minimum value of flank wear occurs as 0.0419 mm. This part of study shows that in machining process of this alloy, there is a strong relationship in between material removal rate and flank wear. Table 2 shows selected optimum parameters including feed rate, depth of cut and cutting speed taken from Fig.3 (the Pareto front) corresponding measured outputs (Flank wear, Material removal rate, Surface roughness).

Table 2. Some selected optimal cutting parameters

V_c (m/min)	f (mm/rev)	a_p (mm)	V_B (mm)	MRR (mm^3/min)	Ra (µm)
63.12	0.102	1.50	0.066	9655	0.7994
79.10	0.109	1.42	0.096	12138	0.7947
95.66	0.105	1.44	0.155	15473	0.7962
117.95	0.108	1.43	0.223	18367	0.7997
130.53	0.105	1.50	0.298	20658	0.7990

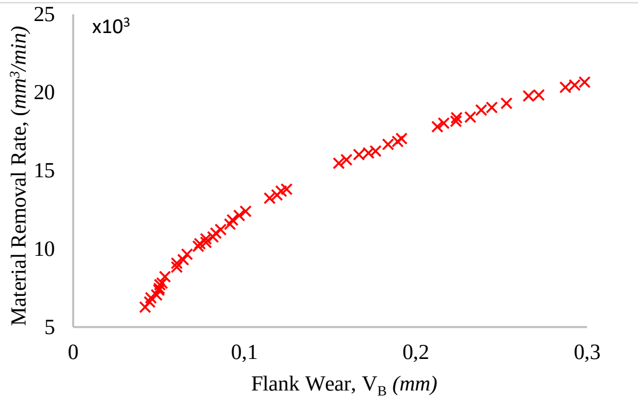

Figure 3. The Pareto front of non-dominated solutions for machining parameters.

4.2. Minimizing Power Consumption

Power consumption plays an important role to evaluate the sustainability of process. Reducing power consumption is one of the element of sustainable machining process [3]. Thus, it is aimed to minimize power consumption while there are constraints for flank wear, surface roughness and material removal rate in this part of study. The constraint of material removal rate is 10^4 mm^3/min that provides most of non-dominated flank wear values as shown in Fig. 3. Power consumption as kW is calculated by using following well-known equation.

$$P = \frac{F_c V_c}{60x10^3} \tag{15}$$

The optimization model for this case can be stated as follow:

Minimize:	P
Subject to:	$V_B < 0.3$ mm
	$R_a < 0.8$ µm
	MRR > 10^4 mm^3/min
	80 m/min $< V_c <$ 160 m/min
	0.1 mm/rev $< f <$ 0.2 mm/rev
	0.8 mm $< a_p <$ 2 mm

Boundaries of constraints and feasible region are shown in Fig. 4. To achieving minimum power consumption that is 0.454 kW, the lowest values of feed rate and depth of cut must be selected. Cutting speed is 124 m/min at optimum point for fulfil the constraint of material removal rate. Optimum power consumption is obtained when flank wear (VB) is 0.136 mm and surface roughness (Ra) is 0.689 µm. Feasible region illustrated at fixed feed rate that must be 0.1 mm because of constraint of surface roughness that was taken as 0.8 µm. Optimum parameters for minimum power consumption was illustrated as optimum point in Fig.4.

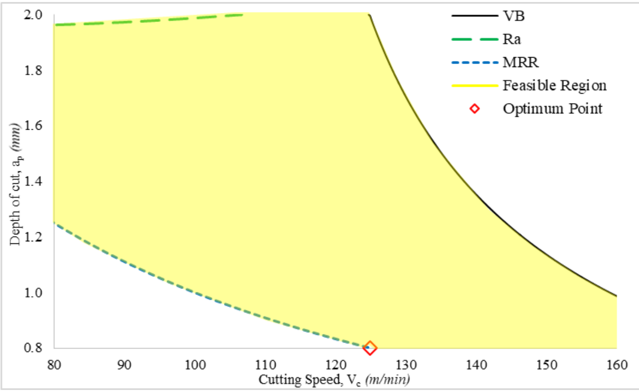

Figure 4. Illustration of feasible region and optimum point for power consumption at 1 mm/rev of feed rate.

5. CONCLUSIONS

Ti-5553 alloy is considered as difficult-to-machine material. Therefore, randomly selected parameters or parameters based on experience does not help to improve machining performance of this new generation titanium alloy. Therefore, this study focuses on the optimizing process parameters in machining process of Ti-5553 alloy. In this study, two cases are taken into account. In the case study I, a set of optimum cutting parameters are obtained for minimum flank wear and maximum material removal rate under constraint of surface roughness (0.8 µm) in turning of Ti-5553 using multi-objective genetic algorithm. This optimization study provided the possible maximum material removal rate. From this part of study, constraint value of material removal rate is also determined. In the case study II, cutting parameters were optimized to minimize power consumption taken constraint value of material removal rate into account. This study demonstrated that power consumption can be substantially reduced by optimizing process parameters.

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