Cutting parameters of milling process optimization to minimize material removal power for AISI 1045 steel

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Abstract. In the machining process, the proper selection of cutting parameters can significantly reduce power consumption. Over the past several years, numerous researchers have devoted considerable attention to optimizing cutting parameters for milling processes to save energy consumption. The correct selection of these parameters is a crucial approach to achieving an optimal machining process. This article presents a study on the optimization of cutting parameters in the milling process of AISI 1045 steel under wet conditions. The aim is to identify an ideal combination of cutting parameters that minimizes the material removal power (P_m). Taguchi and Genetic Algorithm (GA) with two different selection methods are proposed for optimizing four cutting parameters namely cutting depth 'a_p', width of cut 'a_e', cutting speed 'v_c', and feed per tooth 'f_z'. The results demonstrated that GA with tournament selection successfully identifies the optimal cutting parameters, resulting in lower P_m, compared to GA with stochastic selection. The findings of this study provide valuable insights that could lead to more energy-efficient machining processes, contributing to both cost savings and environmental sustainability.

Keywords: Milling, Genetic Algorithm, Cutting parameters optimization.

1 Introduction

Metal cutting is a crucial process in the manufacturing industry, but it requires a significant amount of energy [1]. According to the Energy Information Administration (EIA) report in 2017, this industrial sector will continue to account for the biggest percentage of energy consumption (E_c) worldwide until 2040 [2]. However, the energy efficiency of metal cutting remains relatively low. Therefore, improving this efficiency through optimization of machining processes has become one of the primary goals globally in the manufacturing sector. For machining processes, optimal selection of cutting parameters is a key energy conservation strategy. Studies have shown that variations in cutting parameters result in a significant impact on 'E_c' in the machining process. [3, 4]. Optimizing settings conditions, tools, and tool trajectory can reduce overall 'E_c' by 6 to 40% [5]. Additionally, a proper selection of processing parameters may enhance tool life, reduce manufacturing costs and CO2 emissions, and increase the efficiency of production [6].

Various methods have been employed by researchers to solve optimization problems, principally based on metaheuristic approaches such as Genetic Algorithms (GA), Neighborhood Cultivation Genetic Algorithm (NCGA), Tabu Search (TS), Simulated Annealing (SA), and Gray Wolf Optimization (GWO). For example, a study conducted by Deng et al. [7] used the GA optimization technique to improve machining parameters in multi-pass dry milling operations. The aim of their work was to achieve a balance between processing time, 'E_c', and carbon emissions based on Principal Component Analysis (PCA), and regression analysis of experimental data. In another study, Zhang et al. [8] used a hybrid cuckoo search and grey wolf optimization algorithm (CS-GWO) to find the optimal setting parameters to reduce overall 'E_c' in micro-milling processes. Their findings demonstrated that using the proposed optimization methodology for micro-milling reduces 'E_c' by 7.89% compared to the traditional empirical selection method for cutting parameters. Nguyen et al. [9] presented an integrated strategy using Grey Relation Analysis (GRA), 'PCA', and Desirability Approach (DA) to generate weighted objectives and forecast optimal values of machining process parameters. Four machining process parameters, including cutting velocity, feed rate, depth of cut, and tool nose radius are considered for optimization to simultaneously improve power factor (PF), reduce 'E_c', and improve machining quality by reducing surface roughness (Ra) for dry machining of stainless steel 304. The results indicated that feed rate and cutting velocity had the most significant impact on the technical outcomes, leading to reductions of approximately 34.85% in 'E_c' and 57.65%

in ‘Ra’, while the ‘PF’ improved by about 28.83%. The study proposed by Hu et al. [10] used SA to achieve cutting parameter optimization to decrease machining energy consumption (MEC) with a constant material removal rate (MRR) in the end face turning process. The experiments showed that SA has over 96% probability of obtaining the global optimum, with a 14.03% reduction in end face turning energy consumption (EFTEC) for a given case.

The present paper aims to optimize the cutting parameters, namely depth of cut ‘a_p’, width of cut ‘a_e’, cutting speed ‘v_c’, and feed per tooth ‘ f_z’, during the face milling of the AISI 1045 workpiece material under wet cutting conditions. The GA method and the Taguchi approach, which are widely adopted optimization techniques, were utilized to minimize power consumption.

The rest of this research paper is structured as follows: the next section presents the mathematical model of the material removal power. The calibration of parameters for the suggested technique is studied in Section 3, while Section 5 offers a discussion of the achieved results. The final section includes the conclusion.

2 Mathematical model optimization of Face-Milling Process

Many variable factors are brought into play in the machining process on CNC lathes. The correct selection of cutting parameters has a considerable influence on cutting performance and machining quality, making it the most important variable to be optimized [11]. This article therefore focuses on the optimization of variables including ‘a_p’, ‘a_e’, ‘v_c’, and ‘ f_z’.

2.1 Objective function

To assess the energy consumption of a machine tool, it is essential to understand the power characteristics of its components. These characteristics are influenced not only by the machine's internal composition and operating variations but also by the workpiece and machining conditions [3]. In this paper, the material removal power (P_m) is considered as the objective to be minimized of the face milling process. This objective is represented by the exponential function of process parameters, which can be expressed in Equation 1.

$$P_m = C_p \times v_c^{w_p} \times f_z^{y_p} \times a_p^{x_p} \times a_e^{u_p} \tag{1}$$

Where C_p, w_p, y_p, x_p and u_p are coefficients of P_m , v_c, f_z, and a_e, respectively. Multiple linear regressions on the measured power data can be used to determine these unknown coefficients. These data are measured from the experiments carried out with different combinations of cutting parameters. In our research, the value of these coefficients is obtained from experiments conducted by Lv et al. [12]. The following Table 1 presents the coefficients and data relevant to milling of AISI 1045 steel.

Table 1. Experimental data [12]

Name	Information	
Cutting material	Grade	45
Cutting condition	water-based cutting fluid	
coefficients	C_p	4.044
	w_p	0.958
	y_p	0.798
	x_p	0.923
	u_p	1
Cutting tool	Brand	Carbide tungsten steel
	Cutting diameter	14 mm
	Number of tool teeth	4
	Cutting edge length	35
	Total tool length	100
Machine tool	Brand	XHK- 714F

2.2 Constraint Conditions

When selecting machining parameters, it is important to consider both the performance of the processing system and the technical requirements of the part to be machined. These requirements include factors such as the performance range of the computer numerical control and the durability of the tool, which must be used with care and under limited conditions. These constraints are expressed in equations 2 to 5.

$$f_{z,min} \leq f_z \leq f_{z,max} \tag{2}$$

$$a_{p,min} \leq a_p \leq a_{p,max} \tag{3}$$

$$a_{e,min} \leq a_e \leq a_{e,max} \tag{4}$$

$$v_{c,min} \leq v_c \leq v_{c,max} \tag{5}$$

Where $f_{z,min}$ and $f_{z,max}$ represent the lower and upper limits of the feed per tooth, respectively, $a_{p,min}$ and $a_{p,max}$ specify the depth of cut limits. Similarly, $a_{e,min}$ and $a_{e,max}$ refer to the width of cut limits, while $v_{c,min}$ and $v_{c,max}$ indicate the bounds of cutting speeds, respectively.

Table 2. Cutting parameters and their corresponding ranges/values

Cutting parameters	Unit	Range/values
f_z	mm/tooth	0.03-0.12
a_p	mm	0.5-2.0
a_e	mm	6-12
v_c	m/min	60-120

3 Proposed solution algorithm

3.1 Genetic Algorithm

GA is a widely used optimization tool inspired by the principles of natural genetics, operating based on "survival of the fittest" [13]. This powerful mathematical algorithm is employed to tackle complex problems and optimization tasks [14]. Based on the concept of evolution, GA has been adapted into a computational algorithm aimed at finding solutions to problems, often referred to as objective functions. These algorithms find applications across various domains, including science, engineering, business, economics, and finance. In the field of manufacturing and machining processes, GA has been extensively investigated and used for optimization optimization purposes. Its main operators are the probability of crossover (Pc), the probability of mutation (Pm), the total number of generations (Max_iter), and population size (N_Pop). It is essential for the researcher to select appropriate GA parameters, in addition to considering weighting factors and constraints, to ensure the algorithm operates efficiently [15]. In this study, the GA was employed to address the optimization problem due to its effective global search capability. Subsequently, the milling parameters were optimized utilizing Python software.

3.2 Algorithms parameters calibration: Taguchi

Taguchi method is widely used in experimental engineering design and analysis and aims to determine the parameters that produce optimum levels of quality characteristics with minimal change. The method was proposed by Taguchi in 1993. Taguchi is based on two powerful and fundamental tools: the first is the orthogonal array (OA) and the second is the signal-to-noise ratio (S/N). OAs enable experiments to be planned efficiently, through selection of the levels of factors to be tested in order to minimize the number of trials required to obtain meaningful results. In other words, orthogonal arrays enable experiments to be designed optimally, reducing wasted resources and time. The S/N ratio measures the deviation of a quality characteristic from an expected value. Once again, this is a characteristic that can be divided into three categories: the higher is the better (HTB), the nominal is the better (NTB), and the lower is the better (LTB). For each category, the optimal level of process parameters is the level that yields the highest value of the S/N ratio transformation. Additionally, the S/N plot is used to visually determine the levels that will allow the process to maintain its target value.

Since this study focuses on a minimization problem, the S/N ratio is calculated using the ‘LTB’ criterion. The S/N ratio is calculated as follows:

$$S/N = -10log_{10}(\frac{1}{n}\sum_{i=1}^{n}\frac{1}{y_i^2}) \quad (6)$$

Where 'y' and 'n' represent the observed data and the number of observations, respectively.

Four levels were specified for each factor of the Genetic algorithm for two selection methods (tournament and stochastic selection), as given in Table 3. The parameter levels were selected based on the recent review article conducted by Abdelaoui et al. [16].

Table 3. Genetic Algorithm factor levels (tournament and stochastic selection)

Factors	Level 1	Level 2	Level 3	Level 4
N_Pop	100	200	300	500
Pc	0.6	0.7	0.8	0.9
Pm	0.01	0.05	0.1	0.2
Max_iter	300	400	500	600
Penalty	100	1000	10000	100000

The orthogonal array chosen is L16, with 16 lines corresponding to the number of parameter combinations, as shown in Table 4.

Table 4. Orthogonal array L16 of Taguchi

Test no.	N_Pop	Pc	Pm	Max_iter	Penalty
1	100	0.6	0.01	300	100
2	100	0.7	0.05	400	1000
3	100	0.8	0.1	500	10000
4	100	0.9	0.2	600	100000
5	200	0.6	0.05	500	100000
6	200	0.7	0.01	600	10000
7	200	0.8	0.2	300	1000
8	200	0.9	0.1	400	100
9	300	0.6	0.1	600	1000
10	300	0.7	0.2	500	100
11	300	0.8	0.01	400	100000
12	300	0.9	0.05	300	10000
13	500	0.6	0.2	400	10000
14	500	0.7	0.1	300	100000
15	500	0.8	0.05	600	100
16	500	0.9	0.01	500	1000

Five crucial control factors have been identified, including 'N_Pop', 'Max_iter', 'Pc', 'Pm', and 'Penalty' along with the independent use of tournament and stochastic selections. The obtained results from applying the Taguchi method to these two conventional genetic algorithms (GAs) are depicted in Figures 1 and 2.

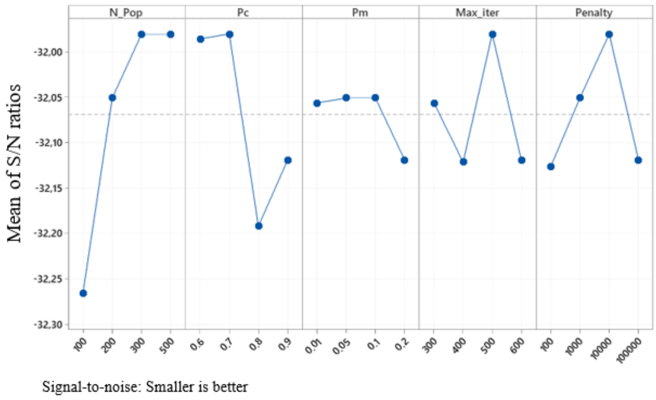

Fig.1. The mean S/N plot of GA-Tournament

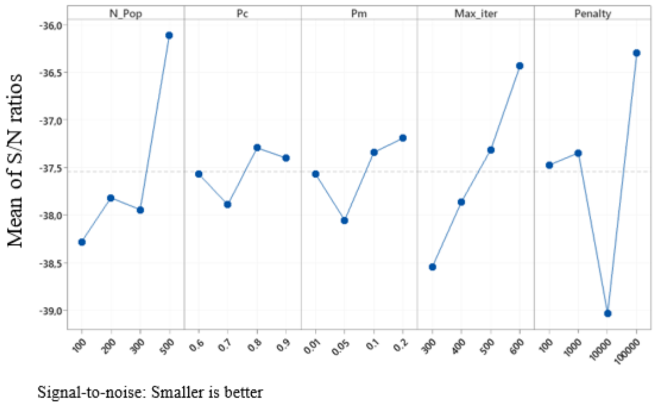

Fig.2. The mean S/N plot of GA-Stochastic

From Fig.1, it is evident that higher population sizes are more conducive to achieving optimal results. Regarding mutation probability, it is advisable to set it at 0.1, while the crossover probability should not surpass 0.7. Additionally, setting the penalty factor and number of iterations at higher levels, specifically 10000 and 500 respectively, proves beneficial. Fig.2 further emphasizes the importance of higher levels for population size, mutation probability, number of iterations, and penalty, which are set at 500, 0.2, 600, and 100000 respectively. However, the crossover probability still be capped at 0.8. Table 5 regroups the optimal factor levels for the two genetic algorithm selection methods.

Table 5. Optimal parameters for suggested optimization algorithms

Factors	GA-Stochastic	GA-Tournament
N_Pop	500	500
Pc	0.8	0.7
Pm	0.2	0.1
Max_iter	600	500
Penalty	100000	10000

4 Results and discussions

The proposed model with the constraints and the GA parameter values are defined in the previous section. In this part, optimal cutting parameters and their respective effects are discussed.

4.1 Optimal cutting parameters for milling AISI 1045 steel

Table 6 presents the optimal values of cutting parameters for steel material obtained using two different selection methods of the genetic algorithm: stochastic and tournament selection.

For the stochastic selection method, the optimal ‘ f_z’ is 0.038 mm/tooth, ‘v_c’ is 62.379 m/min, ‘a_p’ is 0.5002 mm, and ‘a_e’ is 7.568 mm. The minimum P_m achieved with these parameters is 62.3 W. On the other hand, for the tournament selection method, the optimal ‘ f_z’ is 0.03 mm/tooth, ‘v_c’ is 60.017 m/min, ‘a_p’ is 0.5001 mm, and ‘a_e’ is 6.0008 mm. The minimum of P_m achieved with these parameters is 39.4 W. The table indicates also that different selection methods of the genetic algorithm lead to variations in the optimal cutting parameters and consequently, variations in the power consumption during the cutting process.

Comparing the results, it's evident that the tournament selection method yields superior performance, as it achieves a lower power consumption of 39.4 W compared to 62.3 W with the stochastic selection methodology. This highlights the effectiveness of the tournament selection methodology in optimizing the cutting parameters for reduced power consumption.

It is important to note that for both selection methods, the cutting parameters fall within the specified ranges. Notably, the program selects the minimum values within these ranges, indicating an optimization for minimizing power consumption during the cutting process.

Table 6. Optimal cutting parameters

Cutting parameters	GA Stochastic	GA Tournament
f_z (mm/tooth)	0.038	0.03
v_c (m/min)	62.379	60.017
a_p (mm)	0.5002	0.5001
a_e (mm)	7.568	6.0008
Minimum P_m (W)	62.3	39.4

4.2 Impact of cutting parameter on material removal power consumption

The impact of cutting parameters on power consumption has been illustrated in Figures 3, 4, and 5 and analyzed in this study. To examine this effect, the width of cut was kept constant while the other three parameters (v_c, f_z, a_p) were considered as variables. The obtained results from the tournament selection method were selected for this analysis, given its demonstrated capability to yield optimal results in terms of optimization.

The 3D plot illustrates a surface plot where the depth of cut is fixed at 5 mm, while ‘f_z’ and ‘v_c’ are varied. The plot represents the relationship between these two variable parameters and the resulting power consumption (Fig.1). As the values of ‘f_z’ and ‘v_c’ change, the power consumption varies accordingly, with minimizing ‘f_z’ and ‘v_c’ leading to a decrease in power consumption. This indicates that reducing the feed per tooth and cutting speed results in lower power consumption during the milling process. Similarly, when decreasing ‘a_p’ and ‘f_z’ while keeping ‘v_c’ constant, power consumption also decreases (Fig.2). Additionally, Fig.3 demonstrates that power consumption decreases with lower values of ‘v_c’ and ‘a_p’ while keeping ‘f_z’ constant.

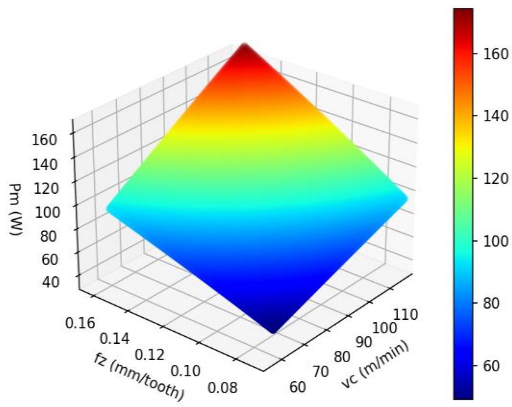

Fig.3. Impact of f_z and v_c on material removal power

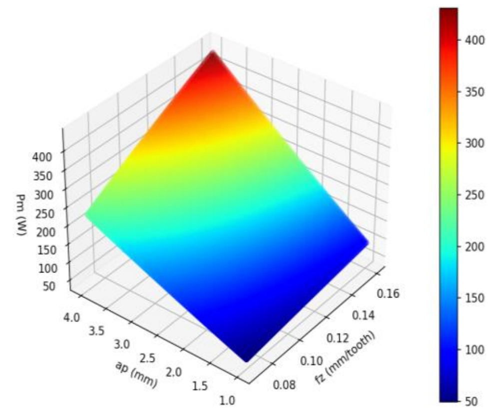

Fig.4. impact of f_z and a_p on material removal power

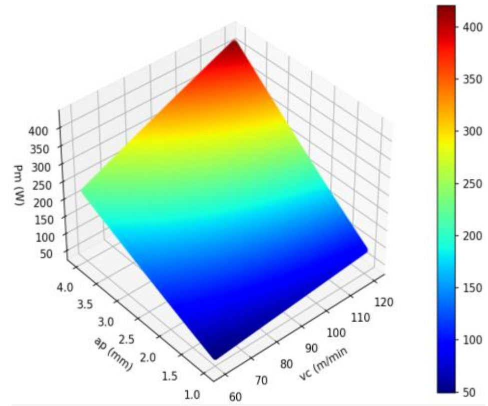

Fig.5. Impact of v_c and a_p on material removal power

5 Conclusion

Mechanical processing is an important pillar of mechanical manufacturing, plays a vital role in the manufacturing industry, and requires a large amount of electrical energy. Cutting parameters have a significant impact on the productivity and energy efficiency of machine tools. Indeed, the judicious selection of these parameters can help to optimize energy consumption in manufacturing processes. In this paper, a single optimization model is established, taking the four cutting parameters namely cutting depth 'a_p', width of cut 'a_e', cutting speed 'v_c', and feed per tooth 'f_z' as optimization variables and low material removal power as optimization objective. The model is optimized using the traditional Genetic Algorithm with two different selection techniques, and the Taguchi method is employed to calibrate the parameters of these techniques. Case analysis revealed that GA with tournament selection effectively identifies the optimal combination of cutting parameters, achieving lower material removal power in the milling process of AISI 1045 under wet cutting conditions, compared to GA with stochastic selection.

Future research will focus on incorporating methodologies to generate feasible solutions within our optimization tool. In addition, this study could be expanded to apply this optimization approach to a broader range of materials and cutting conditions, including various steels, alloys, and machining environments. It could also extend to other material removal processes, such as grooving, contouring, drilling, etc. Exploring advanced or hybrid optimization techniques may further enhance the model's robustness and effectiveness across different manufacturing scenarios.

References

1. Li JG, Lu Y, Zhao H, et al (2014) Optimization of cutting parameters for energy saving. Int J Adv Manuf Technol 70:117–124.
2. Dr. Ian Mead AA for EA, U. (2017) Key takeaways : IEO2017 Reference case. 42
3. Zhou L, Li J, Li F, et al (2017) An improved cutting power model of machine tools in milling process. Int J Adv Manuf Technol 91:2383–2400.
4. Zhou G, Lu Q, Xiao Z, et al (2019) Cutting parameter optimization for machining operations considering carbon emissions. J Clean Prod 208:937–950.
5. Li C, Xiao Q, Tang Y, Li L (2016) A method integrating Taguchi, RSM and MOPSO to CNC machining parameters optimization for energy saving. J Clean Prod 135:263–275.
6. Han F, Li L, Cai W, et al (2020) Parameters optimization considering the trade-off between cutting power and MRR based on Linear Decreasing Particle Swarm Algorithm in milling. J Clean Prod 262.
7. Deng Z, Zhang H, Fu Y, et al (2017) Optimization of process parameters for minimum energy consumption based on cutting specific energy consumption. J Clean Prod 166:1407–1414.
8. Zhang X, Yu T, Dai Y, et al (2020) Energy consumption considering tool wear and optimization of cutting parameters in micro milling process. Int J Mech Sci 178:105628.
9. Nguyen TT, Mia M, Dang XP, et al (2020) Green machining for the dry milling process of stainless steel 304. Proc Inst Mech Eng Part B J Eng Manuf 234:881–899.
10. Hu L, Cai W, Shu L, et al (2021) Energy Optimisation For End Face Turning With Variable Material Removal Rate

Considering the Spindle Speed Changes. Int J Precis Eng Manuf - Green Technol 8:625–638.
11. Jia S, Wang S, Lv J, et al (2022) Multi-objective optimization of CNC turning process parameters considering transient-steady state energy consumption. Sustain 13.
12. Lv J, Jia S, Wang H, et al (2021) Comparison of different approaches for predicting material removal power in milling process. Int J Adv Manuf Technol 116:213–227.
13. Tamang SK, Chandrasekaran M, Palanikumar K, Arunachalam RM (2019) Machining performance optimisation of mql-assisted turning of inconel-825 superalloy using ga for industrial applications. Int J Mach Mach Mater 21:43–64.
14. Dinc A, Mamedov A (2021) Optimization of surface quality and machining time in micro-milling of glass. Aircr Eng Aerosp Technol.
15. Yusup N, Zain AM, Hashim SZM (2012) Evolutionary techniques in optimizing machining parameters: Review and recent applications (2007–2011). Expert Syst Appl 39:9909–9927.
16. abdelaoui FZ El, Jabri A, Barkany A El (2023) Optimization techniques for energy efficiency in machining processes—a review. Springer London