PSO Based Improved Surface Roughness Measuring Approach of Manufactured Product Within CP Factory Using T6 6068 Aluminium

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Abstract. This paper presents a methodology to obtain improved quality of surface roughness during production of mobile case cover inside a Cyber Physical (CP) factory using micro-CNC end milling with aluminium alloy T6 (6068). The said machining is done with different machining parameters such as cutting velocity, Spindle speed and cut depth. Three profile parameters (R_a, R_z and R_{zmax}) are projected as response variables. Thereafter, Taguchi's orthogonal array design is considered with smaller-is-better Signal to Noise ratio and linear regression is performed to get optimal process parameter settings combination. This result is further verified using a Particle Swarm Optimization (PSO) technique and validation is done on CNC machining center.

Keywords: Surface Roughness, CP Factory, Particle Swarm Optimization.

1 Introduction

Milling is an important metal removing technology among the different machining approaches for the manufacturing companies. In modern era the traditional milling has been replaced by Computer numerical controlled (CNC) milling which automates the cutting process and decreases the machining time, minimize variation in process, enhance product quality and boost the productivity of manufacturing processes [1]. The most common CNC milling operation is end-milling because of its high-speed metal cutting rate with accurate surface finish, which is generally used for creating various geometrical shapes in the workpiece by incorporating different types of sub-operations such as milling, drilling, reaming, profiling, chamfering, slotting, etc. [2] [3]. Surface roughness is an important parameter that needs to be considered during end milling operation as, majority of manufacturing industries considered surface roughness (R_a) as an important machining attribute, and it is responsible for the improved product quality and reduced cost of manufacturing. Various machining conditions such as cutting velocity, feed rate, spindle speed, machine vibration and depth of cut greatly influence the surface roughness in the end milling process [4], which are not only responsible for producing the good surface finish for end products but can also increase the tool life. In the recent year, the optimization of milling processes is evolving in tremendous rate, which further amplified the interest among manufacturing companies and researchers.

After careful investigation on milling processes it is found that different types of milling tools are being used according to the shape or geometry of the product design. Pillai et. al [5] used end milling cutting process of Aluminium workpieces using a multi-axis milling center to establish a set of optimum process parameter combinations using the Taguchi-Grey Relational Analysis to analyze the performance variables such as processing time and surface roughness influenced by different process factors such as spindle speed, feed rate and tool path scheme. Okokpujie et.al. [6] developed mathematical model based on the least square approximation method and Response Surface Methodology (RSM) that predicted the R_a for the end milling using spindle speed, axial depth of cut (axial and radial) and feed rate for Al 6061 alloy. Kumar et.al [7] utilized Taguchi technique for optimization of the end milling process parameters, which are coolant, feed rate, spindle speed and depth of cut for milling of SS-304. Qehaja et. al. [8] studied the influence of spindle speed, feed rate, depth of cut and hardness of workpiece material on the R_a in the CNC end milling by developing the R_a based mathematical model. Wojciechowski et. al. [9] studied ball end milling process and demonstrated the relationships between the instantaneous tool displacements and Ra where the cutting surface is inclined to the axis of the tool. Li and Zhu [10] estimated cutting force for five axis milling process using a flat end milling tool and coupled the result with the cutting effects. Gao et. al. [11], conducted various slot milling experiments using Aluminium 7075 with chamfered tool at different chamfer length, considering tool wear and R_a as the process responses. Das et al. [12] conducted CNC milling of alumina green ceramic compact, where process factors such as spindle speed, 3 axis speed (along x, y, and z), and depth of cut were investigated. For performance characteristic the authors have used surface roughness and developed a regression model. Further they performed Genetic Algorithm based optimization of the R_a.

From the above study it could be stated that, R_a is the essential performance characteristic for the CNC milling process. There are different other surface parameters that could be considered during the investigation of surface roughness, such as mean roughness depth (R_z) and maximum roughness depth (R_{zmax}). Hence it is important to analyze the influence of different machining parameters on the various surface roughness coefficients such as R_a, R_z and R_{zmax}. The objective of this research is to incorporate various parametric combinations during different end milling conditions and record the surface roughness values using a stylus based profilometer. Further the comparison would be carried out with the responses to find the ideal process parameters for the end milling. The analysis will be performed using Taguchi's orthogonal design and regression analysis. The obtained results would be verified using a Particle Swarm Optimization (PSO) based algorithm.

The rest of this paper is organized as, section #2, which portrays the detailed explanation on the experimental set-up on CNC milling machine, material, and the input parameters are explained, section #3, which depicts the methodologies applied in this research and the results and discussions and finally section #4, which concludes this work with future scopes.

2 Material and Method

The machining is carried out on a CNC micro milling machine (Proxxon FF 500/BL). It is a three axis CNC milling center with 50μm precision and has brushless direct drive (Fig. 1). It has a large transverse area (X- 290mm, Y-100mm, and Z-200mm). The surface profile is measured using an electronic profilometer Handysurf E-35B, manufactured by Carl Zeiss, Japan. The surface profile measurement parameters are selected according to three standard, ISO 4287-1997, DIN EN ISO 4287 AND JIS B0601.

2.1 Material

Aluminium alloy 6082 (T6) is used as the test workpiece for machining. The dimension of the aluminium alloy block is 160×80×15 mm^3. This material is primarily used for machining in highly stressed application. The chemical composition by percentage of weight of 6082 (T6) are Al (95.1% - 98.2%), Si (0.71% - 1.29%), Mg (0.59% - 1.195%), Mn (0.39% - 0.99%), Fe (0.1% - 0.5%), Cr (0.05% - 0.25%), Zn (0.01% - 0.2%), Ti (0.01% - 0.1%), Cu (0.05% - 0.1%) and other (0%-0.15%). Further Table 1 portrays the mechanical properties of Aluminium alloy 6082(T6) [13]. The proposed products are machined and recreated inside the CP factory which are mobile case covers, originally made with plastic. The 3D design files of the workpieces are obtained from Festo (Fig. 2a and 2b). These designs are made with solidworks. The exterior dimension of the product is (11.4×60×11.7 mm^3).

Fig. 1. CNC setup with NCCAD 9

Table 1. Mechanical property of aluminium alloy 6082(T6)

Tensile strength	Yield strength	Shear strength	Elastic modulus	Poisson's ratio	Elongation
330 MPa	270 Mpa	220Mpa	69 Gpa	0.33	9.8%

2.2 Experiments

The preparation of work piece is done using the CNC machining center. The CNC milling machine uses NCCAD 9 software where, the input of the 3D model and other different cutting factors such as tools, cutting speed, cut depth etc. are defined and with respect to these inputs a tool path is generated. For machining two major cutting tools are used in the experiments (Fig. 3). The tools are made of high-speed steel 12mm for material removal and 4mm for geometric shaping respectively. cutting speed (CS) and spindle speed (SS) are selected within range of 150 ≤ CS ≤ 280 and 3500 ≤ SS ≤ 4000 and depth of cut (DOC) is fixed at 0.3mm. Using Taguchi's L9 orthogonal design, a total of nine experiments are carried out on nine samples (Table 2). The surface roughness values (R_a, R_z and R_{zmax}) are recorded using Handysurf for every experimental trial and portrayed in Table 2.

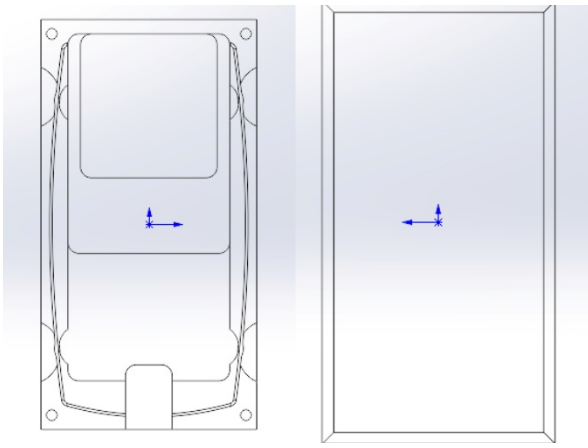

Fig. 2. 3D model of the product

Fig. 3. Cutting Tools

Table 2. Taguchi's L^9 orthogonal design for experiments

No. of Run	Process parameters		Response parameters		
	Cutting velocity	Spindle speed	Surface roughness (Ra)	(Rz)	Rzmax
1	150	3500	0.583	2.453	3.197
2	150	3800	0.463	2.097	2.273
3	150	4000	0.383	2.000	2.467
4	200	3500	1.000	4.710	7.653
5	200	3800	0.776	3.427	5.433
6	200	4000	0.653	2.943	5.217
7	280	3500	1.266	5.273	8.613
8	280	3800	0.943	4.260	7.757
9	280	4000	0.783	3.713	6.680

3 Methodology and Results

In this paper the optimization is carried out using Taguchi's design of experiment and further the obtained result is verified using a PSO algorithm. Eberhart and Kennedy [14] introduced PSO to the research community, which is based on natural phenomenon and population derived stochastic optimization method. PSO imitates the actions of a swarm of birds. It has many similar features of GA. PSO begins with a swarm or group of solutions or particles generated using a random function. It further leads to the peak or valley area in quest of best solutions. In general, all the particles go by the finest one and fly through the problem space. All of the particles have their own positions and fitness scores and have velocities which fix the flying direction of the particles. Following are the velocity and position updating expressions,

$$v_i^t = w \times v_i^{t-1} + c1 \times [P_{best} - x_i^{t-1}] + c2 \times [G_{best} - x_i^{t-1}] \quad (1)$$

$$x_i^t = x_i^{t-1} + v_i^t \quad (2)$$

Each particle of the swarm updates its position with respect to two near-optimal particles, (1) the best fitness scoring particle of the swarm in current iteration, which is termed as the P_{best} and (2) the best particle with finest fitness score in all iterations, which is termed as the global best or G_{best} [15]. The PSO flowchart obtained from [15] as,

START
Step 1. Define the fitness function $f(x)$, $X=(x_1, x_2, ..., x_d)^T$
Step 2. Initialize the swarm of particles x_i, $(i = 1, 2, ..., n)$ and velocity v_i
Step 3. Define the w, c1, c2 (inertial and learning parameters)
Step 4. While (t< maximum number of iteration) do
Step 5. for each particle x_i in the swarm do
Step 6. Generate new particle using Eq. (1), (2)
Step 7. if $f(xi)<f(x_{best})$ then (f is objective function)
Step 8. Accept the new solution
Step 9. end
Step 10. end
Step 11. end
Step 12. return the global best bat x_{best}
STOP

3.1 Results and Discussion

Taguchi's orthogonal array design is employed to obtain the response tables for means and signal-to-noise ratios (Table 3(a) and 3(b)). For the problem in hand, surface roughness is a minimization type response. Hence smaller-is-better SN-ratio is selected as optimization approach.

Table 3. Response tables for (a) S-N Ratio (b) Means

(a)

Level	**Cutting velocity**	**Spindle Speed**
1	-5.961	-12.387
2	-12.210	-10.265
3	-14.179	-9.699
Delta	8.218	2.688
Rank	1	2

(b)

Level	**Cutting velocity**	**Spindle Speed**
1	1.768	3.861
2	3.535	3.048
3	4.365	2.760
Delta	2.597	1.101
Rank	1	2

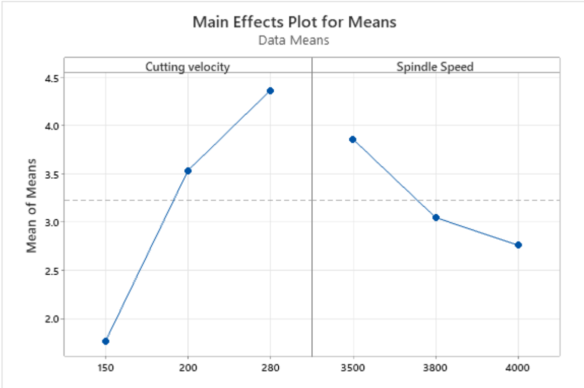

Fig. 4. Effects plot for means

The main effect plot is portrayed in Fig. 4 which states that the best R_a values are obtained at cutting velocity =150 and Spindle Speed=4000. Further regression equations (R^2 values > 70%) are obtained for all the response parameters (R_a, R_z and R_{zmax}) which are portrayed in eq. (3)-(5). These equations can be used to predict the response parameters value with different values of process parameters.

$$R_a = 2.555 + 0.003853 \times \text{Cutting Velocity} - 0.000691 \times \text{Spindle Speed} \quad (3)$$
$$R_z = 9.60 + 0.01614 \times \text{Cutting Velocity} - 0.002554 \times \text{Spindle Speed} \quad (4)$$
$$R_{zmax} = 10.82 + 0.03699 \times \text{Cutting Velocity} - 0.00348 \times \text{Spindle Speed} \quad (5)$$

These equations are used to generate the objective function of the PSO which is portrayed in eq. (6). For the PSO, the parameters are selected based on the recommendation provided in [14], w=rand(), c1=0.45, c2=0.55, swarm size= 1000, Iteration count = 500.

$$f = 0.33 \times (R_a + R_z + R_{zmax}) \quad (6)$$

The PSO algorithm is substantially quick (< 10 Sec. CPU time) and obtains the optimal solution which is not different than the Taguchi's optimization. The response values are R_a=0.369, R_z=1.805, R_{zmax}=2.4485 obtained using regression eq. (3)-(5), which are substantially close to the experimental values (Table 2). The convergence curve is presented in Fig. 5. The final products are portrayed in Fig. 6(a) and 6(b).

4. Conclusions

This paper presents an experimental machining process optimization approach within the production of CP factory. The product manufactured is a mobile phone case cover which is recreated using the micro-CNC end milling facility and T6 aluminium alloy (6068). Different process variables such as cutting velocity, spindle speed and cut depth are considered for CNC milling and various surface roughness parameters (R_a, R_z and R_{zmax}) are considered as process responses. Taguchi's orthogonal design is carried out using smaller-is-better SN ratio for optimization and linear regression is performed to obtained the response equations. Further a PSO algorithm is employed to verify the result obtained from Taguchi's analysis. This research concludes that, the better surface finish is obtained with lower cutting velocity (150 m/min) and higher spindle speed (4000 RPM). This work is aimed to extend with additional process variables such as tool size, process vibration, in the future. Also, 3D profile analysis would be another area which will be explored further.

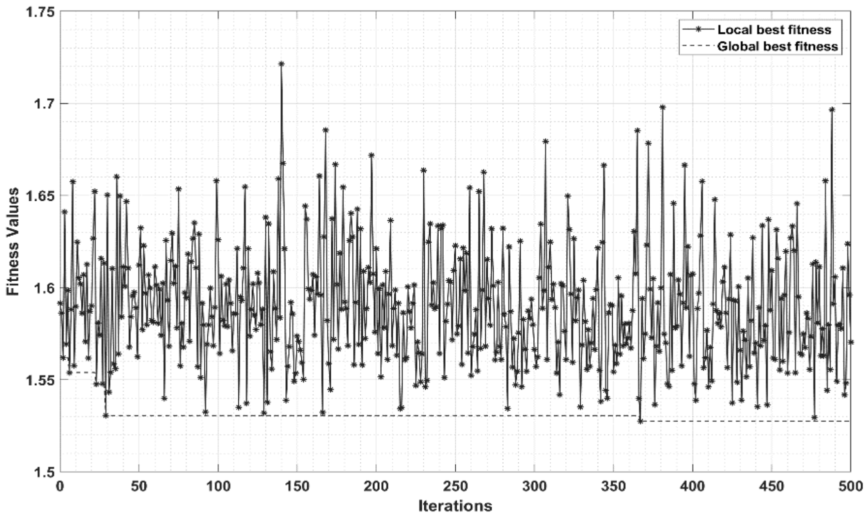

Fig. 5. PSO Convergence Plot

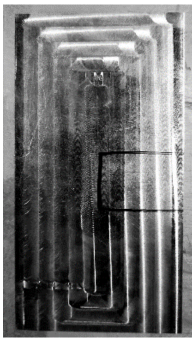

Fig. 6. (a) flat surface

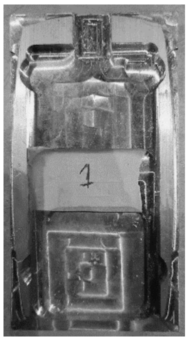

Fig. 7. (b)inner side of product

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