SURFACE ROUGHNESS ANALYSIS IN END MILLING WITH RESPONSE ANT COLONY OPTIMIZATION

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ABSTRACT

The increase of consumer needs for quality metal cutting related products (more precise tolerances and better product surface roughness) has driven the metal cutting industry to continuously improve quality control of metal cutting processes. Within these metal cutting processes, the end-milling process is one of the most fundamental metal removal operations used in the manufacturing industry. Surface roughness also affects several functional attributes of part such as contact causing surface friction, wearing, light reflection, heat transmission ability of distributing holding and lubricant, coating, or resisting fatigue. Therefore, the desired finish surface is usually specified and the appropriate processes are select to reach the required quality.This paper presents the optimization of the surface roughness when milling Mould Aluminium alloys (AA6061-T6) with Response Ant Colony Optimization (RACO). The approach is based on Response Surface Method (RSM) and Ant colony Optimization (ACO). In this work, the objectives were to find the optimized parameters and find out the most dominant variables (cutting speed, federate, axial depth and radial depth). The first order model indicates that the feedrate is the most significant factors effecting surface roughness. The optimised minimum and maximum values that predicted by RACO were 0.36 μm and 1.37 μm.

Keywords: Response Surface Method, Ant colony optimisation, Surface roughness, Optimised

INTRODUCTION

Roughness plays an important role in determining how a real object will interact with its environment. Rough surfaces usually wear more quickly and have higher friction coefficients than smooth surfaces. Roughness is often a good predictor of the performance of a mechanical component, since irregularities in the surface may form nucleation sites for cracks or corrosion. Although roughness is usually undesirable, it is difficult and expensive to control in manufacturing. Decreasing the roughness of a surface will usually exponentially increase its manufacturing costs. This often results in a trade-off between the manufacturing cost of a component and its performance in application.

Planning the experiments through the design of experiments has been used quite successfully in process optimization by Chen and Chen [1], Fung and Kang [2], Tang et al. [3], Vijian and Arunachalam [4], Yang [5] as well as Zhang et al. [6], etc. Four controlling factors including the cutting speed, the feed rate, the depth of cut, and the cutting fluid mixture ratios with three levels for each factor were selected. The Grey relational analysis is then applied to examine how the turning operation factors influence the quality targets of roughness average, roughness maximum and roundness. An optimal parameter combination was then obtained. Additionally, the ANOVA was also utilized to examine the most significant factors for the turning process as the roughness average, roughness maximum and roundness are simultaneously considered.

Aslan et al. [7] used an orthogonal array and the analysis of variance (ANOVA) to optimization of cutting parameters in turning hardened AISI 4140 steel (63 HRC) with Al_2O_3 + TiCN mixed ceramic tool. The flank wear (VB) and surface roughness (Ra) had investigated a process optimization to determine optimal values of cutting parameters, such as cutting speed, feed rate and depth of cut. Nalbant et al. [8] used Taguchi method to find the optimal cutting parameters for surface roughness in turning operations of AISI 1030 steel bars using TiN coated tools. Three cutting parameters, namely, insert radius, feed rate, and depth of cut, are optimized with considerations of surface roughness, and so on. However, very few studies have been conducted to investigate roundness under different turning parameter. Additionally, cutting fluids properly applied by Kalpakjian and Schmid,[9] and EI Baradie,[10], can increase productivity and reduce costs by choosing higher cutting speeds, higher feed rates and greater depths of cut. Effective application of cutting fluids can also increase tool life, decrease surface roughness, increase dimensional accuracy and decrease the amount of power consumed. The water-soluble (Water-miscible) cutting fluids are primarily used for high speed machining operations because they have better cooling capabilities [10]. There fluids are also best for cooling machined parts to minimize thermal distortions. Water-soluble cutting fluids are mixed with water at different ratios depending on the machining operation. Therefore, the effect of water-soluble cutting fluids under different ratios was also considered in this study.

Recent investigation performed by Alauddin *et al.* [11] has revealed that when the cutting speed is increased, productivity can be maximised and, meanwhile, surface quality can be improved. According to Hasegawa *et al*. [12], surface finish can be characterised by various parameters such as average roughness (Ra), smoothening depth (Rp), root mean square (Rq) and maximum peak-to-valley height (Rt). The present study uses average roughness (Ra) for the characterisation of surface finish, since it is widely used in industry. By using factors such as cutting speed, feed rate and depth of cut, Hashmi and his coworkers [13, 14] have developed surface roughness models and determined the cutting conditions for 190 BHN steel and Inconel 718. EI-Baradie [15] and Bandyopadhyay [16] have shown that by increasing the cutting speed, the productivity can be maximised and, at the same time, the surface quality can be improved. According to Gorlenko [17] and Thomas [18], surface finish can be characterised by various parameters. Numerous roughness height parameters such as average roughness (Ra), smoothening depth (Rp), root mean square (Rq), and maximum peak-to-valley height (Rt) can be closely correlated. Mital and Mehta [19] have conducted a survey of the previously developed surface roughness prediction models and factors influencing the surface roughness. They have found that most of the surface roughness prediction models have been developed for steels.

RESPONSE SURFACE METHOD

This is a method for obtaining an approximate function using results of several numerical calculations to increase calculation efficiency and thereby implementing design optimization. In the response surface method, design parameters are changed to formulate an approximate equation by the design of experiment method. An approximate sensitivity calculation of a multicrestedness problem can be performed using a convex continuous function and applied to optimization. The Box-Behnken Design is normally used when performing non-sequential experiments. That is, performing the experiment only once. These designs allow efficient estimation of the first and second –order coefficients. Because Box-Behnken design has fewer design points, they are less expensive to run than central composite designs with the same number of factors. Box-Behnken Design do not have axial points, thus we can be sure that all design points fall within the safe operating. Box-Behnken Design also ensures that all factors are never set at their high levels simultaneously [20 - 22].

ANT COLONY OPTIMISATION

Ant colony optimization algorithms are part of swarm intelligence, that is, the research field that studies algorithms inspired by the observation of the behavior of swarms. Swarm intelligence algorithms are made up of simple individuals that cooperate through self-organization, that is, without any form of central control over the swarm members. A detailed overview of the self organization principles exploited by these algorithms, as well as examples from biology, can be found in [23].

One of the first researchers to investigate the social behavior of insects was the French entomologist Pierre-Paul Grass´e. In the 1940s and 1950s, he was observing the behavior of termites in particular, the Bellicositermes natalensis and Cubitermes species. He discovered [24] that these insects are capable to react to what he called “significant stimuli,” signals that activate a genetically encoded reaction. He observed [24] that the effects of these reactions can act as new significant stimuli for both the insect that produced them and for the other insects in the colony.

Goss et al. [25] developed a model to explain the behavior observed in the binary bridge experiment. Assuming that after t time units since the start of the experiment, m_1 ants had used the first bridge and m_2 the second one, the probability p_1 for the (m + 1)th ant to choose the first bridge can be given by

$$P_{1(m+1)} = \frac{(m_1 + k)^h}{(m_1 + k)^h + (m_2 + k)^h}$$

where parameters k and h are needed to fit the model to the experimental data. The probability that the same (m+1)th ant chooses the second bridge is $P_{2(m+1)} = 1 - P_{1(m+1)}$. Monte Carlo simulations, run to test whether the model corresponds to the real data [10], showed very good fit for $k \approx 20$ and $h \approx 2$. This basic model, which explains the behavior of real ants, may be used as an inspiration to design artificial ants that solve optimization problems defined in a similar way.

Ant colony optimization has been formalized into a combinatorial optimization metaheuristic by Dorigo et al. [26, 27] and has since been used to tackle many combinatorial optimization problems (COPS). Given a COP, the first step for the application of ACO to its solution consists in defining an adequate model. This is then used to define the central component of ACO: the pheromone model. The model of a COP may be defined as follows:

A model $P = (S, \Omega, f)$ of a COP consists of

- a search space S defined over a finite set of discrete decision variables and a set Ω of constraints among the variables;
- an objective function $f: S \rightarrow \mathcal{R}_0^+$ to be minimized

Ant System was the first ACO algorithm to be proposed in the literature [28 - 30]. Its main characteristic is that the pheromone values are updated by all the ants that have completed the tour. The pheromone update for τ_{ij} , that is, for edge joining cities i and j, is performed as follows:

$$\tau_{ij} \leftarrow (1-\rho).\ \tau_{ij} + \sum_{k=1}^{m} \Delta\tau_{ij}^{k}$$

where ρ is the evaporation rate, m is the number of ants, and $\Delta\tau_{ij}^{k}$ is the quantity of pheromone per unit length laid on edge (i, j) by the kth ant:

$$\Delta\tau_{ij}^{k} = \begin{cases} \dfrac{Q}{L_k}, & if ant\ k\ used\ edge\ (i,j) in\ its\ tour \\ 0, & otherwise \end{cases}$$

where Q is a constant and L_k is the tour length of the kth ant.

EXPERIMENTAL SETUP

The 27 experiments were carried out on Haans machining centre with 6-axis as shown in Figure 1. The water soluble coolant was used in these experiments. Each experiment was stopped after 90 mm cutting length. For the surface roughness measurement surface roughness tester was used. Each experiment was repeated three times using a new cutting edge every time to obtain accurate readings of the surface roughness. The physical and mechanical properties of the workpiece are shown in Table 1 and Table 2. After the preliminary investigation, the suitable levels of the factors are used in the statistical software to deduce the design parameters for Aluminum Alloys (AA6061-T6) as shown in Table 3. The lower and higher speed values selected are 100 m/s and 180 m/s, respectively. For the feed, the lower value is 0.1 mm/rev and the higher value is 0.2 mm/rev. For the axial depth, the higher value is 0.2 mm and the lower value is 0.1 mm and for the radial depth the higher value is 5 mm and lower value is 2 mm.

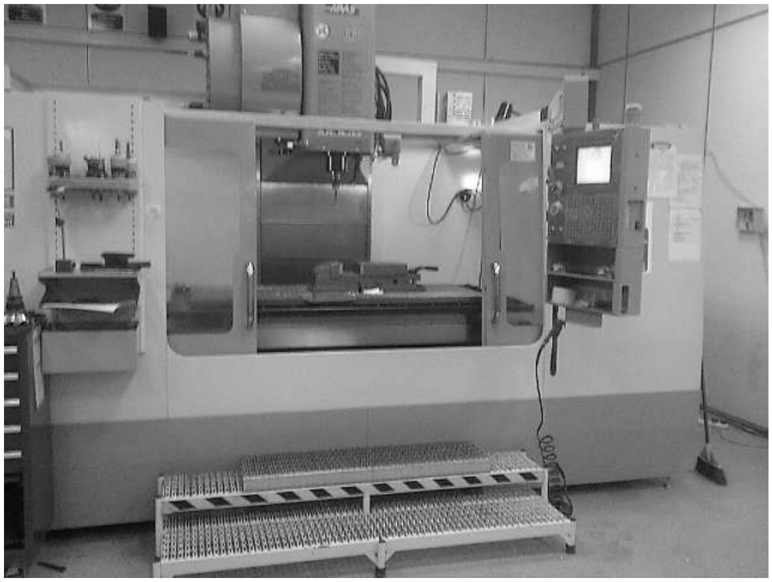

Figure 1: (a) Haans CNC milling with 6-axis

Table 1: Physical properties for workpiece

Component	Al	Cr	Cu	Fe	Mg	Mn	Si	Ti	Zn
Wt %	95.8-98.6	0.04-0.35	0.15-0.4	Max 0.7	0.8-1.2	Max 0.15	0.4-0.8	Max 0.15	Max 0.25

Table 2: Mechanical properties for workpiece

Hardness, Brinell	95
Hardness, Knoop	120
Hardness, Rockwell A	40
Hardness, Rockwell B	60
Hardness, Vickers	107
Ultimate Tensile Strength	310 MPa
Tensile Yield Strength	276 MPa
Elongation at Break	12 %
Elongation at Break	17 %
Modulus of Elasticity	68.9 GPa
Density	2.7 g/cc

Table 3: Design Parameters

Cutting speed (m/min)	Feedrate (mm/rev)	Axial depth (mm)	Radial depth (mm)
140	0.15	0.10	5.0
140	0.15	0.15	3.5
100	0.15	0.15	5.0
140	0.15	0.15	3.5
180	0.15	0.20	3.5
180	0.15	0.15	2.0
100	0.20	0.15	3.5
140	0.15	0.15	3.5
180	0.15	0.15	5.0
100	0.15	0.20	3.5
140	0.20	0.10	3.5
180	0.10	0.15	3.5
140	0.15	0.20	2.0
180	0.15	0.10	3.5
140	0.10	0.15	2.0
140	0.15	0.20	5.0
100	0.15	0.10	3.5
140	0.20	0.15	2.0
100	0.15	0.15	2.0
140	0.20	0.15	5.0
140	0.10	0.10	3.5
140	0.20	0.20	3.5
140	0.15	0.10	2.0
100	0.10	0.15	3.5
180	0.20	0.15	3.5
140	0.10	0.20	3.5
140	0.10	0.15	5.0

RESULTS AND DISCUSSION

After conducting the first pass (one pass is equal to 90 mm length) of the 27 cutting experiments, the surface roughness readings are used to find the parameters appearing in the postulated first order model (Equation 1). In order to calculate these parameters, the least square method is used with the aid of Minitab. The first-order linear equation used to predict the surface roughness is expressed as:

$$R_a = 0.5764 + 0.0049C_{speed} + 47.69f + 58.45a_{depth} + 1.08r_{depth} \qquad (1)$$

Where the C_{speed}, f, a_{depth} and r_{depth} are the cutting speed, feed rate, axial depth and radial depth respectively

Generally, reduction of cutting speed, axial depth of cut caused the larger surface roughness. On the other hand, the increase in feed rate and radial depth caused slightly reduction of surface roughness. The feed rate is the most dominant factors on the surface roughness, followed by the axial depth, cutting speed and radial depth respectively. Hence, a better surface roughness is obtained with the combination of low cutting speed and axial depth, high feed rate and radial depth. Similar to the first-order model, by examining the coefficients of the second-order terms, the feedrate (*f*) has the most dominant effect on the surface roughness. After examining the experimental data, it can be seen that the contribution of cutting speed (C_{speed}) is the least significant. As seen from Figure 2, the predicted surface roughness using the second order RSM model is closely match with the experimental results. It exhibits the better agreement as compared to those from the first-order RSM model. Feed rate versus cutting speed contour plotted for first- order model are shown in Figure 3. It is clearly shown that the relationship between the surface roughness and design variables. The analysis of variance (ANOVA) for firstorder is tabulated in Table 4. It indicates that the model is adequate as the *P*-value of the lack-of-fit is not significant (>0.05).

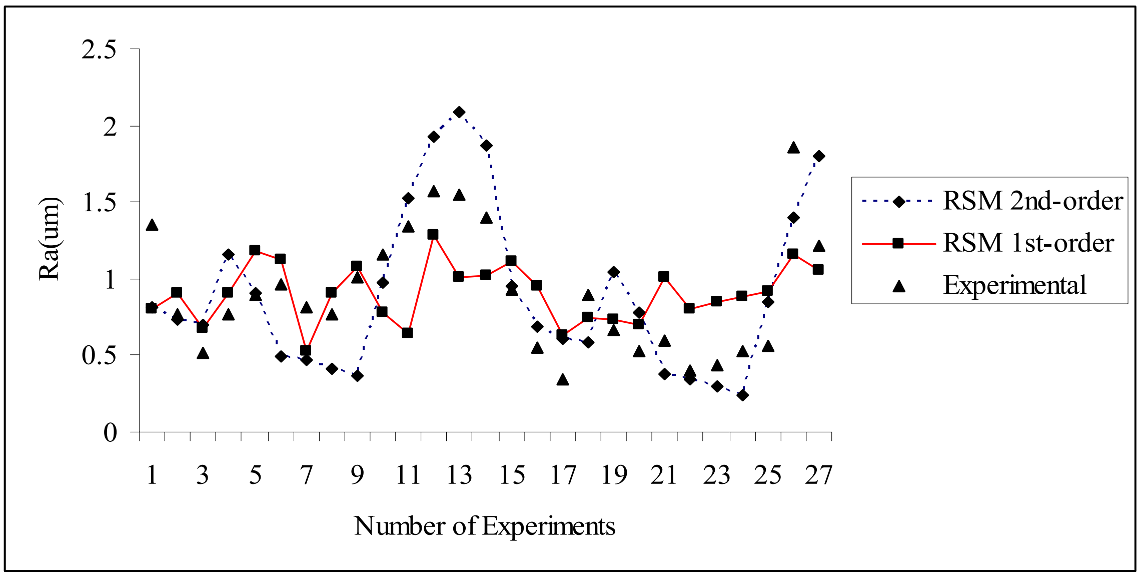

Figure 2: Comparison between the experimental and predicted results

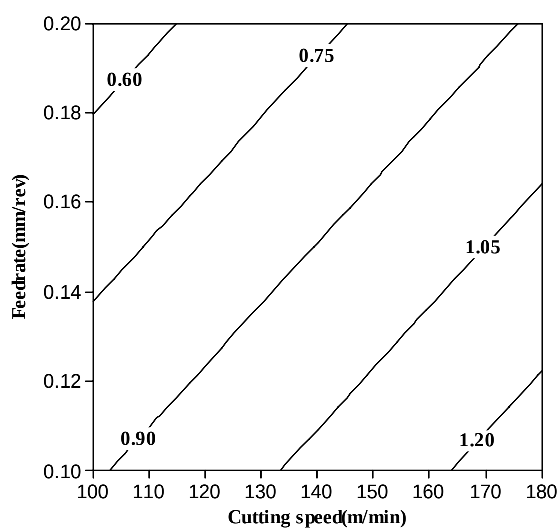

Figure 3: Feed rate versus cutting speed contour plotted for first-order

Table 4: Analysis of variance for first-order equation

Source	**DOF**	**Seq SS**	**Adj SS**	**Adj MS**	***F***	***P***
Regression	4	0.9309	0.9309	0.2327	0.78	0.552
Linear	4	0.9309	0.9309	0.2327	0.78	0.552
Residual Error	22	6.5937	6.5937	0.2997		
Lack-of-Fit	20	6.3151	6.3151	0.3158	2.27	0.351
Pure Error	2	0.2786	0.2786	0.1393		
Total	26	7.5246				

Result validation

The optimized surface roughness model is tested with experimental result. The predicted minimum and maximum surface roughness using optimized tool life model by RACO are compared with the measured surface roughness and their results are reported in Figure 4. The validation experiment is performed in the same machining environment as the training experiment. The errors of surface roughness obtained by optimized min and max surface roughness model are 4.65 and 1.4 %. The optimum cutting parameters for minimum surface roughness are cutting speed 100 m/min; federate 0.2 mm/rev, axial depth 0.1 mm and radial depth 5 mm. On other hand, the optimum parameters for maximum surface roughness are cutting speed 180 m/min; federate 0.1 mm/rev, axial depth 0.2 mm and radial depth 2 mm.

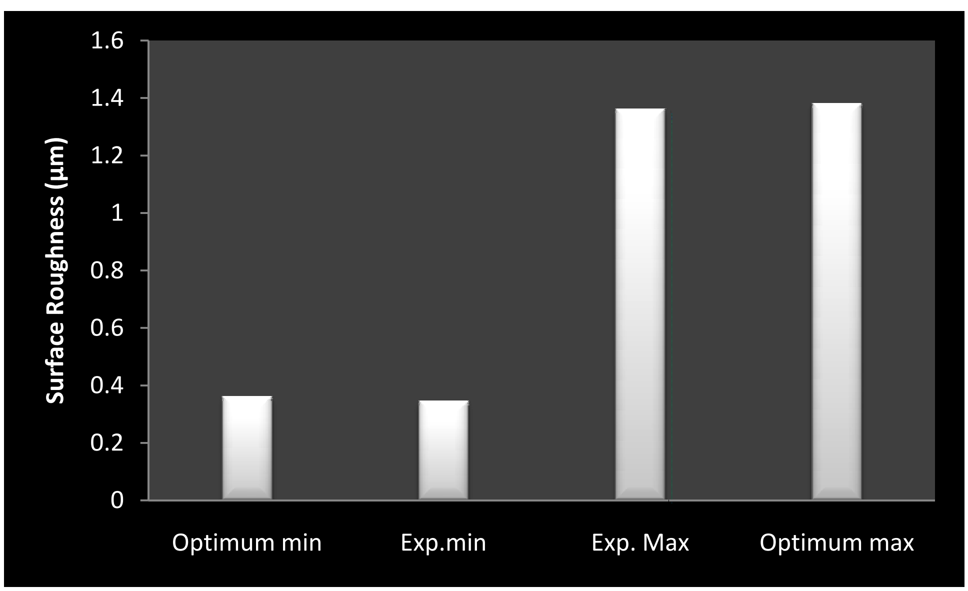

Figure 4: Comparison of minimum and maximum optimised surface roughness with experimental.

CONCLUSION

This research illustrates the machining of Aluminium Alloys (AA6061-T6) with end-milling methods and predicting their subsequent surface roughness. There is becoming a need for investigating the machining of various types of aluminum and their surface roughness which in turn can be useful in developing more cost effective personalized products. The authors have shown the use of RACO to formulate an optimized minimum and maximum surface roughness prediction model for end machining of AA6061-T6. This prediction model is tested on the validation experimental and the error analysis of the prediction result with the measured results is estimated at 4.65 and 1.4 % for minimum and maximum surface roughness which is small and shows the efficacy of the prediction model. Finally, the simulation results show that ACO combine with RSM can be very successively used for reduction of the effort and time required. This means that it can solve many problems that have mathematical and time difficulties.

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