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# Optimization of Surface Roughness in End Milling on Mould Aluminium Alloys (AA6061-T6) Using Response Surface Method and Radian Basis Function Network

K.Kadirgama[a], M.M.Noor[a], N.M.Zuki.N.M[a], M.M. Rahman[a], M.R.M. Rejab[a], R. Daud[a], K. A. Abou-El-Hossein[b]

[a] *Faculty of Mechanical Engineering, Universiti Malaysia Pahang, P. O. Box 12, 25000 Kuantan. Malaysia*

[b] *Mechanical Engineering Department, University of Pretoria, South Africa*

**Abstract**

This paper is concerned with optimization of the surface roughness when milling Mould Aluminium alloys (AA6061-T6) with carbide coated inserts. Optimization of milling is very useful to reduce cost and time for machining mould. The approach is based on Response Surface Method (RSM) and Radian Basis Function Network (RBFN). RBFN was successfully used by Tsoa and Hocheng in their recent research. They used this network to predict thrust force and surface roughness in drilling. In this work, the objectives are to find the optimized parameters, and to find out the most dominant variables (cutting speed, federate, axial depth and radial depth). The optimized value has been used to develop a blow mould. The first order model and RBFN indicates that the feedrate is the most significant factors effecting surface roughness. RBFN predict surface roughness more accurately compared to RSM.



Keywords: Response Surface Method, Radian Basis Function Network, Surface roughness, Optimized

## 1. 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 do. 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 during manufacturing. Decreasing 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.

Recent investigation performed by Alauddin *et al.* [1] has revealed that when the cutting speed is increased, productivity can be maximised, and surface quality can be improved. According to Hasegawa *et al*. [2], 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 [3, 4] have developed surface roughness models and determined the cutting conditions for 190 BHN steel and Inconel 718. EI-Baradie [5] and Bandyopadhyay [6] have shown that by increasing cutting speed, the productivity can be maximised, and the surface quality can be improved simultaneously. According to Gorlenko [7] and Thomas [8], 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 strongly correlated. Mital and Mehta [9] have conducted a survey of 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. Koren *et al.* [10] have proposed a model-based approach to sense tool wear and breakage. Algorithms and on-line training of model-based approach, using artificial intelligence methods, have been suggested by Koren *et al.* [10]. Tarng and Lee [11] have proposed the use of average and median force of each tooth in the milling operation.

* *Corresponding author.; e-mail:* Kumaran@ump.edu.my,

Measured by sensors, the average and median forces of each tooth have been used as input values. An appropriate threshold has been subsequently built to analyse information and detect the tool conditions.

Ko *et al.* [12] have introduced an unsupervised and a self-organised neural network combined with an adaptive time-series AR modelling algorithm to monitor tool breakage in milling operations. The machining parameters and average peak force have been used to build the AR model and neural network. Lee and Lee [13] have used neural network-based approach to show that by using force ratio, flank wear can be predicted within 8% to 11.9% error and by using force increment; the prediction error can be kept within 10.3% of the actual wear. Choudhury *et al.* [14] have used an optical fibre to sense the dimensional changes of the work-piece and correlated it to the tool wear using neural network approach. Dimla and Lister [15] have acquired the data of cutting force, vibration, and measured wear during turning. And neural network has been trained to distinguish the tool state.

## 2. Response Surface Method and RBFN

The Box-Behnken Design is normally used when performing non-sequential experiments i.e. 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 [16 - 18].

Genetic Algorithm (GA) was used to find the optimum weight, momentum, and step size to be used in RBFN. Later the optimum weight would be fed to the RBFN. Then training would be needed until the R.M.S.E reaches a satisfactory value. The training data acquired from Response Surface Method to RBFN mode, and the epoch number was 10,000 [19]. After 1,000 iterations, the RBFN was better enough to produce acceptable results. Transfer function used as sigmoid, but the momentum used was 0.7.

## 3. Experimental Setup

The 27 experiments were carried out on Haans machining centre with 6-axis as shown in Figure 1.a, and $90^0$ tool holder as shown in Figure 1.b. 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 reading of surface roughness. The physical and mechanical properties of the workpiece are shown in Table 1 and Table 2. After the preliminary investigation, suitable levels of factors were used in the statistical software to deduce the design parameters for Aluminium Alloys (AA6061-T6) as shown in Table 3. The lower and higher speed values selected were 100 m/s and 180 m/s, respectively. For the feed, the lower value was 0.1 mm/rev and the higher value was 0.2 mm/rev. For the axial depth, the higher value was 0.2 mm, and the lower value was 0.1 mm. And for the radial depth, the higher value was 5 mm, and lower value was 2 mm.

(a)

(b)

Figure 1. (a) Haans CNC milling with 6-axis ,(b) $90^0$ tool holder

Table 1: Physical properties of workpiece

| | | | | | |
|---|---|---|---|---|---|
| Component | Mg | Mn | Si | Ti | Zn |
| Wt % | 0.8-1.2 | Max 0.15 | 0.4-0.8 | Max 0.15 | Max 0.25 |
| Component | Mn | Si | Ti | Zn | |
| Wt % | Max 0.15 | 0.4-0.8 | Max 0.15 | Max 0.25 | |

Table 3: Design Parameters

| Cutting speed (m/min) | Feedrate (mm/rev) | Axial depth (mm) | Radial depth (mm) |
|---|---|---|---|
| 140 | 0.15 | 0.1 | 5 |
| 140 | 0.15 | 0.15 | 3.5 |
| 100 | 0.15 | 0.15 | 5 |
| 140 | 0.15 | 0.15 | 3.5 |
| 180 | 0.15 | 0.2 | 3.5 |
| 180 | 0.15 | 0.15 | 2 |
| 100 | 0.2 | 0.15 | 3.5 |
| 140 | 0.15 | 0.15 | 3.5 |
| 180 | 0.15 | 0.15 | 5 |
| 100 | 0.15 | 0.2 | 3.5 |
| 140 | 0.2 | 0.1 | 3.5 |
| 180 | 0.1 | 0.15 | 3.5 |
| 140 | 0.15 | 0.2 | 2 |
| 180 | 0.15 | 0.1 | 3.5 |
| 140 | 0.1 | 0.15 | 2 |
| 140 | 0.15 | 0.2 | 5 |
| 100 | 0.15 | 0.1 | 3.5 |
| 140 | 0.2 | 0.15 | 2 |
| 100 | 0.15 | 0.15 | 2 |
| 140 | 0.2 | 0.15 | 5 |
| 140 | 0.1 | 0.1 | 3.5 |
| 140 | 0.2 | 0.2 | 3.5 |
| 140 | 0.15 | 0.1 | 2 |
| 100 | 0.1 | 0.15 | 3.5 |
| 180 | 0.2 | 0.15 | 3.5 |
| 140 | 0.1 | 0.2 | 3.5 |
| 140 | 0.1 | 0.15 | 5 |

## 4. Results and Discussion

The first order linear equation for predicting temperature is expressed as:

$$y = 0.5764 + 0.0049x_1 - 3.5850x_2 + 1.5383x_3 - 0.016x_4 \quad (1)$$

Generally, reduction in cutting speed and axial depth of cut will cause the surface roughness to become larger. On the other hand, increase in feedrate and radial depth will slightly cause a reduction in surface roughness.

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 |

The feedrate has the most dominant effect on the surface roughness followed by the axial depth, cutting speed, and radial depth. A better surface roughness is obtained with the combination of low cutting speed, axial depth, high federate, and radial depth. Figure 2 shows surface roughness values obtained by experimentation and values predicted by first order model and RBFN. It is obvious that the predicted values by RBFN are very close to the experimental readings. The adequacy of first order model is verified using analysis of variance (ANOVA). The model was checked for its adequacy at a 95% level of confidence.

Table 4 indicates that the model is adequate since *P* values of lack-of-fit are not significant and F-statistics is 2.27. This implies that the model could fit and that it is adequate. The optimum value for surface roughness is 0.4261 µm, which corresponds to design variables: Cutting speed (m/min) =100, Feed rate (mm/rev) = 0.2, Axial depth (mm) = 0.1 and Radial depth (mm) = 5.0. The cutting conditions of fine surface in Figure (2.a) are Cutting speed (m/min) =100, Feed rate (mm/rev) = 0.2, Axial depth (mm) = 0.1 and Radial depth (mm) = 5.0 .And the cutting conditions for rough surface in Figure 2.b are Cutting speed (m/min) =140, Feed rate (mm/rev) = 0.15, Axial depth (mm) = 0.15 and Radial depth (mm) = 3.5. The sensitivity test was performed to obtain the variables that affect the surface roughness as shown in Figure 3a. The test shows that federate is the main domain followed by axial depth, radial depth, and cutting speed. Feed rate is the velocity at which the cutter is fed, that is, advanced against the work piece. Surface plot shows the correlation between the variables and response in Figure 3.b. A blow mould has been developed according to optimized parameters. The final product of the blow mould has a surface roughness of 0.45µm as shown in Figure 4. Eventually the time of machining has been reduced with the optimized method.

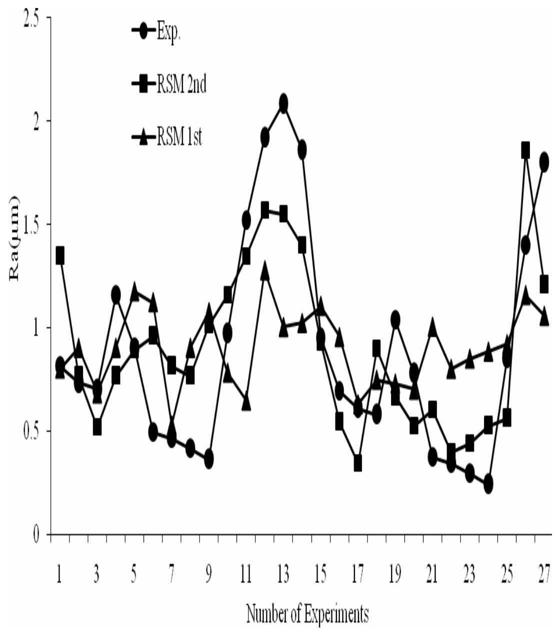



Figure 2: Comparison between experimental results and predicted results (First order & RBFN)

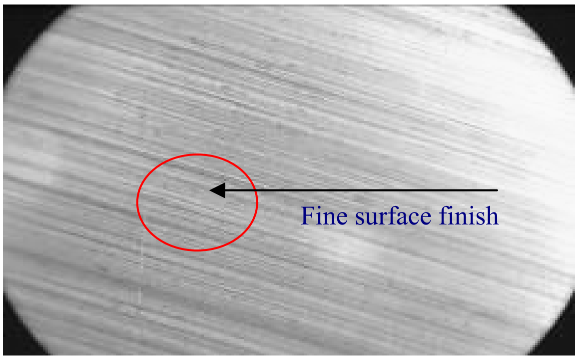
Table 4: ANOVA analysis

| Source | DF | 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 | | | | |

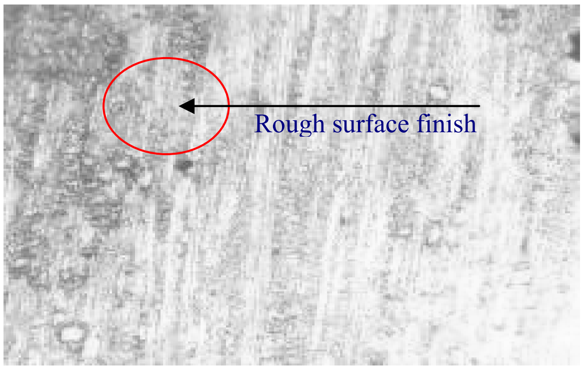
## 5. Conclusion

RBFN has been found to be the most successful technique to perform trend analysis of surface roughness with respect to various combinations of four cutting parameters (cutting speed, federate, axial depth, and radial depth). The models have been found to accurately represent surface roughness values with respect to experimental results.

Both RSM and RBFN model reveal that feedrate is the most significant design variable in determining surface roughness response as compared to others. With the model equations obtained, a designer can subsequently select the best combination of design variables for achieving optimum surface roughness. This eventually will reduce the machining time and save the cutting tools.

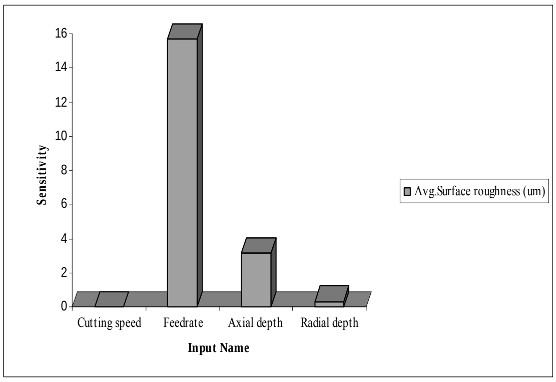



(a)

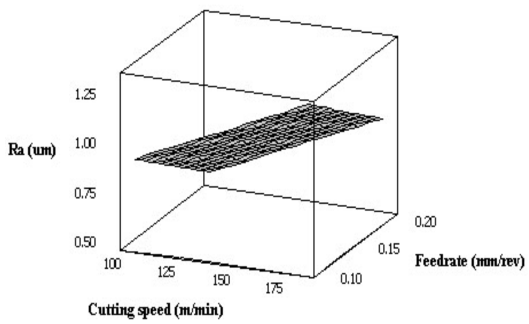



(b)

Figure 2. (a) Fine surface, (b) Rough surface.




(a)




(b)

Figure 3: (a) Sensitivity Test ,(b) Surface plot.

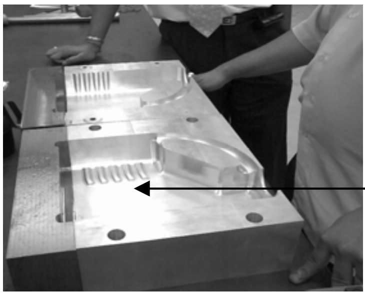



Figure 4: Blow mould


## Acknowledgement

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