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# Evaluation of Power Consumption in High Efficiency Milling (HEM) of Aluminium 6061

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## Abstract

*In the machining industry, reducing energy consumption at a maximal material removal rate (MRR) has long been a priority. Using the response surface method, a predictive model has been proposed for the minimal power consumption in side-milling machining. Using response surface method (RSM), the effect of cutting parameters such as feed rate, spindle speed, and radial depth of cuton power consumption was investigated. The results revealed that feed rateis the most inûuential parameter for power consumption. The higher feed rate, the shorter cycle time thus reduce the power consumption. Based on the optimization model, minimum power consumption of 82.38 kW can be achieved at feed rate = 6,000 mm/in, radial depth of cut of 0.3 mm and spindle speed 12,000 rpm.*

## 1.0 Introduction

With current increases in energy consumption and carbon emission limits, improving the energy efficiency become a priority in manufacturing sector especially on machining process. Energy prices have risen dramatically, forcing industrial companies to consider their energy costs [1]. There are several strategies can be used to lower the energy consumption in machining process by optimization of cutting parameters and minimizing cycle time such as using high-speed machining (HSM) [2]. However, both solutions are inefficient in achieving the industry's need on energy efficiency and better surface quality.

Therefore, high efficiency milling (HEM) strategy may be viewed as a viable option for increased machining efficiency [3], reduce power consumption and better surface quality. In this work, HEM cutting parameters; spindle speed (N) and radial depth of cut (Ae) were evaluated and generated predictive optimization model. The search for the best cutting parameters for targeted responses demands a thorough understanding of the machining process as well as a well-defined link between response and input parameter. Kant and Sangwan [2-4] have suggested a model of multi objective optimization predictive in improving turning process's surface quality and power consumption. They identified that feed rate and depth of cut have extra response compared with cutting speed. Bilga et al. [5] have optimized parameters of cutting speed, feed rate, depth of cut and nose radius in rough turning operation in cutting EN 353 alloy steel by using carbide inserts for power and energy efficiency using ANOVA in Taguchi method.

Taguchi design of experiments (DOE) method was used to develop a method for predicting SR (surface roughness, Ra) during CNC face milling of Al alloy. DOC (depth of cut),

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FR (feed rate), CS (cutting speed), cutting tool engagement and wear, cutting fluid consumption, and the three components of the cutting force were all identified throughout the practical. Standard L27 OA was chosen for a total of six elements, four of which have three levels and two of which have two levels. The research revealed that FR, Fx cutting force, DOC, cutting tool engagement, and cutting fluid consumption were the most influential characteristics [6].

Process parameter optimization using Taguchi technique and ANOVA of ball end mill in machining of hardened steel AISI H11. The control variables were cutting speed, feed rate, depth of cut, and radial depth of cut, whereas the response parameters were surface finish and tool wear. Cutting speed was shown to be the most influencing parameter for tool life and surface finish in the findings analysis [7]. Bhushan et al. [8] utilised RSM and desirability analysis to find the best machining parameters for milling AA7075-15 wt% SIC with a tungsten carbide cutting tool in order to achieve the lowest power consumption and tool wear. Cutting speed was shown to be the most important factor, followed by depth of cut, feed, and nose radius.

Santhakumar and Iqbal [9,10] study trochoidal slotting in machining of AISI D3 steel in the using artiûcial neural network modelling algorithms found that feed rate and RDOC contributed to the lower power consumption and surface roughness. Yan et al. [11] proposed a multi-objective optimization method based and RSM on weighted grey relational analysis to optimise the cutting parameters in the milling process in dry cutting condition for medium carbon steel with a carbide tool in order to achieve the lowest cutting energy, maximum material removal rate, and lowest surface roughness. The results show that the radial depth of the cut has the greatest influence, followed by the depth of the cut, feed rate, and spindle speed. The experimental findings show that RSM and grey relational analysis (GRA) are effective techniques for multi-objective cutting parameter optimization.

Campatelli et al. [12] investigate the impact of feed rate, cutting speed, and radial and axial depth of cutting on energy consumption during carbon steel milling using RSM. The best combination for minimum energy consumption were achieved at values of radial engagement at 1.0 mm and feed of 0.12 mm/tooth. For turning EN-31 steel with a tungsten carbide tool, Abhang and Hameedullah et al. [13] developed a prediction model utilizing RSM. The results reveal that feed rate, depth of cut, tool nose radius, and cutting speed all have a substantial impact on power usage. The second order model was indicated to be further accurate than the first order model in forecasting power consumption during milling.

From the above works on optimization of power consumption, shows a mixed result on the dominant factor for energy consumption in machining. In addition, there are limited study on the predictive model of energy consumption in high efficiency milling process. Therefore, this paper fills this gap and focuses on predictive model of HEM cutting parameters with the aim of minimizing energy consumption inside milling process.

## 2.0 Experimental Test

Experimental on side milling process was conducted using DMU 50 DMG Mori milling machine built-in power logger. Feed rate (Fr), radial depth of cut (Ae) and spindle speed (N) were machining parameters as input variables. The output variable of power consumption (watts) was measured using Celos energy analyzer integrated with the machine.

Solid carbide uncoated flat endmill of 10.0 mm diameter with 3 flutes was utilized in the experiment. To ensure the tool free from any wear defect, visual inspection was performed at every 5th runs of the experiment. The relation between machining parameters and energy consumption were studied based on the face center Central Composite Design (CCD). The CCD includes embedded 2k factorial points (±1), where k is the number of input parameters, center points (0) and axial points (±2). The distance between the center and axial point, $\alpha$ = 1. The parameters and range of the machining used are shown in Table 1.

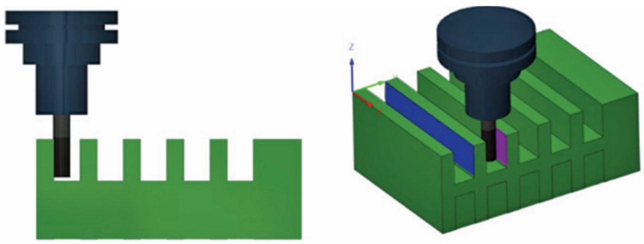

**Figure 1:** Side-milling machining with the application of HEM toolpath

**Table 1: Cutting parameters and range**

| Cutting parameter | Range |
|---|---|
| Feed rate (mm/min) | 2000 to 8000 |
| Radial depth of cut (mm) | 0.3 to 1.0 |
| Spindle speed (rpm) | 8000 to 12000 |

## 3.0 Results and Discussion

The output experimental results are presented in detail in Table 2. The obtained results were analyzeusing the Design-expert statistical analysis software to determine the effect of input parameters and optimization of power consumption.

**Table 2 : Experimental result**

| | RDOC, (mm) | Feed rate, (mm/min) | Spindle speed, (rpm) | Power, (kW) |
|---|---|---|---|---|
| 1 | 0.3 | 2000 | 8000 | 183.91 |
| 2 | 0.3 | 2000 | 12000 | 196.81 |
| 3 | 0.3 | 4000 | 10000 | 118.07 |
| 4 | 0.3 | 6000 | 8000 | 78.14 |
| 5 | 0.3 | 6000 | 12000 | 82.03 |
| 6 | 0.65 | 2000 | 10000 | 180.84 |
| 7 | 0.65 | 4000 | 8000 | 120.89 |
| 8 | 0.65 | 4000 | 10000 | 123.58 |
| 9 | 0.65 | 4000 | 10000 | 112.46 |
| 10 | 0.65 | 4000 | 10000 | 118.81 |
| 11 | 0.65 | 4000 | 10000 | 128.90 |
| 12 | 0.65 | 4000 | 10000 | 106.22 |
| 13 | 0.65 | 4000 | 10000 | 142.56 |
| 14 | 0.65 | 4000 | 12000 | 117.62 |
| 15 | 0.65 | 6000 | 10000 | 90.80 |
| 16 | 1 | 2000 | 8000 | 203.86 |
| 17 | 1 | 2000 | 12000 | 201.04 |
| 18 | 1 | 4000 | 10000 | 136.20 |
| 19 | 1 | 6000 | 8000 | 100.89 |
| 20 | 1 | 6000 | 12000 | 103.14 |

The influence of the input parameters on the power consumption (P) response was investigated using the Analysis of Variance (ANOVA) as shown in Table 3. ANOVA results showed that the model of F value of 448.12 implies that the model is significant and in quadratic. Lack of fit of 0.5383 also indicated that the model is fit for analysis of energy feed rate (Fr) has the most significant impact on power (P), followed by radial depth of cut (RDOC). The different between adjusted $R^2$ value of 0.9895 and predicted $R^2$ value of 0.9849 is less than 0.2 which indicated for adequate signal for model prediction. Equation (1) is obtained for prediction analysis.

$$\text{Power, } P = 287.28 + 24.62\ \text{RDOC} - 0.064\ \text{Fr} + 4.9\text{x}10^{-6}\ \text{Fr}^2 \quad \ldots (1)$$

The effect of feed rate and radial depth of cut is plot as 3D surface plot shownin Fig.2. It shows that power consumption dropped significantly with increasing of feed rate from 2000 to 6,000 mm/min. This can be explained by the shorter machining time with the raising of feed rate. The result

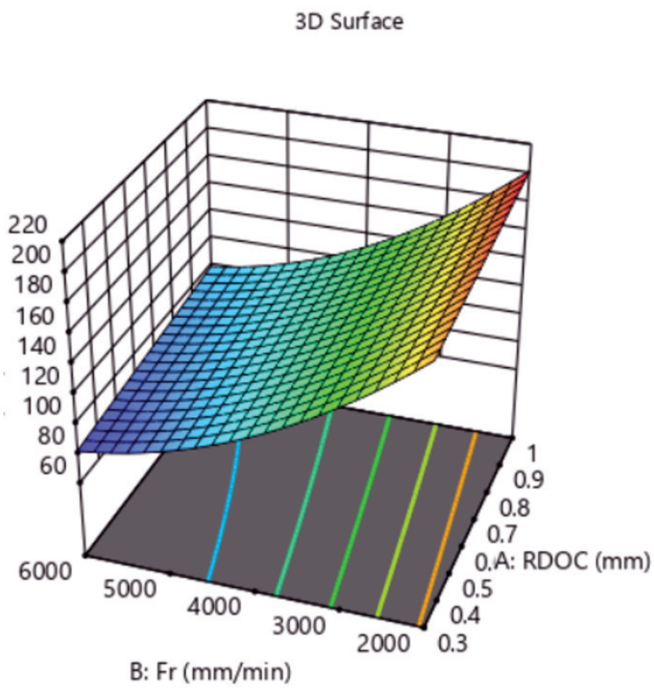


Fig.2 Effect of feed rate and radial depth of cut on power consumption

**Table 3: ANOVA results for the power consumption (P) Reduced Quadratic model**

| Source | Sum of square | F value | P value | % Contr. |
|---|---|---|---|---|
| model | 28104.31 | 448.12 | < 0.0001 | |
| A-RDOC | 942.65 | 60.12 | < 0.0001 | 1.71 |
| B-Fr | 25054.03 | 1597.95 | < 0.0001 | 45.33 |
| $A^2$ | 153.57 | 9.79 | 0.0069 | 0.28 |
| $B^2$ | 780.00 | 49.75 | < 0.0001 | 1.41 |
| Res. | 235.18 | | | 0.43 |
| Lack of fit | 121.92 | 0.5383 | 0.8108 | |

$R^2$ 0.9286, Adjusted $R^2$ 0.8957, Predicted $R^2$ 0.8268 match with the previous work [6-8]. However, the decrease of RDOC slightly affected on power consumption. Power dropped from 60 to 80 kW at RDOC of 1.0 to 0.3 mm respectively. Spindle speed is not significant factor since P>0.05.

The optimization was set to achieve minimum power consumption at maximum material removal rate. The optimal region values have the overall desirability value of 0.966 indicating proximity to target response. The optimum cutting parameter values achieved and the surface roughness value corresponding to these optimum values are presented in Table 4. These optimum values are implemented in confirmation experiments to validate the optimize values. The percent error for power consumption was 4.3% and surface roughness 4.08 %.

**Table 4: Optimum cutting parameters**

| Fr, mm/min | RDOC, mm | N, rpm | P, kW |
|---|---|---|---|
| 6,000 | 0.3 | 12,000 | 82.38 |

## 4.0 Conclusion

The model developed highlights that to acquire a lower power consumption it is necessary to choose maximum feed rate and minimum RDOC that resulting maximum MRR and shorter machining time. The optimum conditions observed to be at 6000 mm/min feed rate, 0.3mmradial depth of cut and 12,000 rpm spindle speed. The predictive equations are developed and are experimentally verified showing +4.3% and 4.08% as the relative errors for power consumption.

## 5.0 Acknowledgement

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