# OPTIMIZATION EXPERIMENTAL STUDY OF MACHINING ENERGY CONSUMPTION OF ZIG-ZAG MILLING CUTTING PATH USING RSM

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## ABSTRACT

*Machining operations in CNC milling which remove the work material require power and energy to activate the machine components such as spindle motor, table and tool movement in order to withstand the high friction and load between tool and work material. Energy consumption during cutting operation is greatly influenced by the machining condition and parameters. This experimental research aims to investigate how energy responds to changes in the machining parameters such as depth of cut, spindle speed, and feed rate during face milling operation of CNC machine. The high-speed steel (HSS) tool with a 10mm diameter was used to face mill the 40mm x 40mm of Aluminum 6061. The design of experiment technique using Response Surface Methodology (RSM) is utilized to optimize the experimental work. Power usage and machining time were recorded for each machining process, which is then used to determine the machining energy consumption. The interaction between machining parameter and energy is comprehensively visualized using surface and contour plot. Additionally, the ANOVA analysis investigates the feed rate as the most influential parameter to the machining energy. Finally, the regression equation of machining energy is generated with reliability (R) value of 0.88 which can be used as an energy prediction model.*

**Keywords**: *Machining Energy, Milling Machining, Response Surface Methodology*



## 1.0 INTRODUCTION

The manufacturing sector consumes 31.8 percent of global energy consumption in 2019, which accounts for approximately one-third of total global energy consumption. Therefore, the industrial sector contributes 29.2 percent of $CO_2$ emissions from energy generation. Sustainable energy consumption models, which have gained importance as a result of industry and research viewpoints, are now being investigated as potential solutions to reverse these detrimental effects of energy consumption [1]. Meanwhile, machining and its sub-operations utilize the most energy in the manufacturing business. To ensure the sustainability of energy production in this situation, energy-efficient techniques must be used during machining operations.

Aside from that, Liu Z.Y. et al [2], identified the energy consumption characteristics for hard milling of tool steel. They classified machining energy consumption into three categories: machine tool, spindle, and process. The combined energy consumption of these three machine levels makes up the machine tool's energy consumption. The energy used to rotate the machine's motor and spindle is referred to as the spindle level energy. The spindle motor, which uses 15% of


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the electricity used by the entire machine tool, rotates the milling cutting tool [3]. It is specifically consumed at the process level by material removal in the production of machined surfaces and chip creation.

Meanwhile, Chu H. et al[4], conducted an investigation into the impact of machining time and energy consumption along the machining process route. They utilized the energy prediction model and processing time to stablish a flexible process planning method. The application of a multi-objective algorithm is utilized to ascertain the optimization of objectives related to low energy consumption and low processing time. The validity of the proposed flexible process planning method was verified using case study, which demonstrated a high level of validity.

The machining energy is dependent on the power usage. Moradnazhad & Unver[5] determined the energy consumption rate by collecting the power consumption data and categorizing CNC milling machine into sub-units. The power graph displays six sub-units namely; switch on, spindle start, spindle accelerate, start machining, material removal rate start, and cease machining [6]. Meanwhile, Pavanaskar & McMains [7] plotted the power versus time graph and highlighted three categories: before the cutting procedure, during the cutting process, and after the cutting process as in Figure 1. Each section has its unique plotting line which represents the exclusive CNC milling machine power utilization depending on the machine component movement and process. This power – time relation graph represents the power characteristic of machine tool which is critical for identifying the power system to achieve the lowest possible power consumption [8][9]. The electrical power can be determined through the relationship between electrical voltage and current using Equation 1. Meanwhile, the electrical energy of machine tool can be identified using Equation 2 or represented by the area under the power versus time graph.

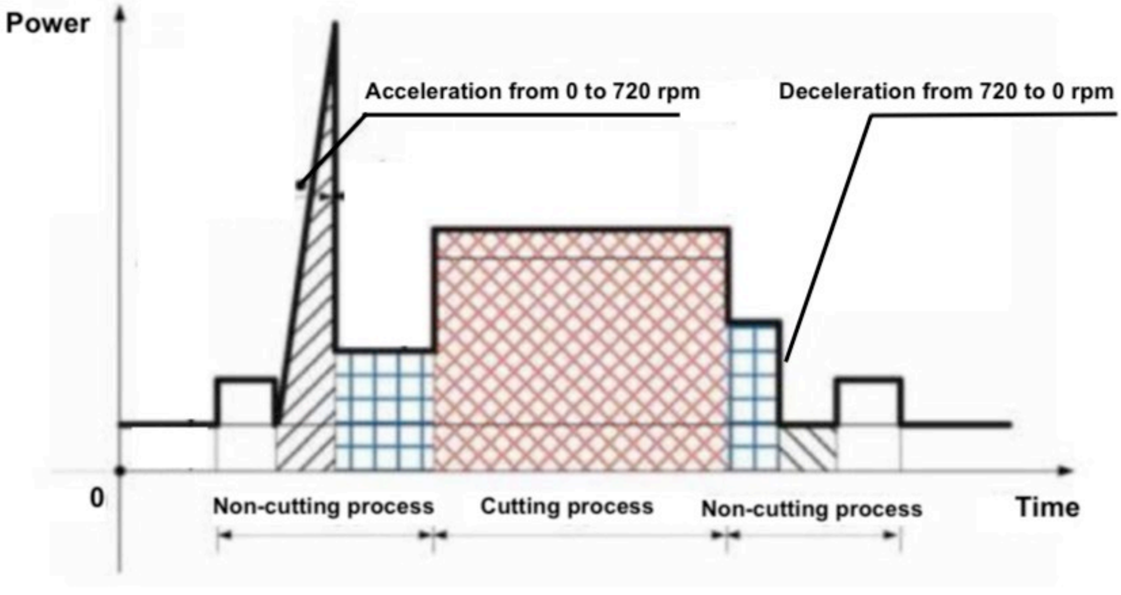


**Figure 1:** Graph of power usage versus time of machine tool [7]

$$\text{Electrical Power, } P = \text{Voltage } (V) \text{ x Current } (A) \tag{1}$$

$$\text{Electrical Energy, } E = \text{Power } (P) \text{ x time } (t) \tag{2}$$

The correlation between energy consumption and material removal rate (MRR) has garnered increased attention due to the significance of MRR as a measure of machining operation efficiency. Pawan S. et al [10] developed a formulation for multi objective optimization model of machining energy consumption (Ecdry) and material removal rate, MRR. The combination of


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Taguchi and Gey relation analysis methods was applied to gather the cumulative performance of MRR and Ecdry. Determining their optimal conditions is beneficial for facilitating more informed decision-making. The result indicates that a marginal increase of 10% Ecdry led to a 99.97% improvement in MRR. Based on the analysis of variance, it was found that the depth of cut is the most influential parameter, followed by feed rate, cutting speed and radius of tool nose.

On the other hand, Wang et al [11] conducted research on the energy consumption and material removal rate during gear horning process. They proposed the theoretical model of energy usage and material removal efficiency and it was validated by the physical gear horning experiment. This research aims to provide in-depth knowledge of the relationship between energy consumption and process parameters, as well as the material removal in the abrasive material honing process.

In addition, Minquiz G.M. et al[12] investigated the tool life performance over machining and tooling costs under dry cutting operation. The design of experiment (DoE) approach was applied to physical milling cutting operation to establish the power demand equation model. It was then used to evaluate alternative machining conditions which showed that the use of good tool condition slightly reduced the machining energy by 0.11kWh and minimized CO2 emission by 0.055kg. This model is useful to predict carbon dioxide emission prior to cutting operation, thus reducing the machining footprint.

Additionally, Tian Y. et al[13] have identified that the specific energy is elevated, leading to reduced energy efficiency in grinding machining operations. A proposed energy prediction model for the grinding process incorporates various grinding-specific movements, such as cutting-out and cutting-in along the spindle, stable cutting, and infeed. Four verification tests were conducted to demonstrate the accuracy of the energy model, revealing an error rate of only 5%.

Furthermore, Cozzolino E. et al,[14] studied the energy of milling operation for finishing the surface of EBM Ti6Ai4V which is produced by additive manufacturing. The varying parameters such as depth of cut, spindle rotational speed and cutting speed were considered to examine the impact on energy machining. They divided energy into 2 conditions which are energy during machining and non-machining. The result proved that it is not sustainable to choose the minimum depth of cut to obtain a fixed total depth of material removed as non-machining time has been proven to play a crucial role in the total energy consumption during the milling process.

Meanwhile, Zhoa J. et al [15], investigated the machining energy consumption adaptive to workpieces, process parameters. The multi-dimension model of energy was established by considering the workpieces, machine tools, processes and influential factor of energy consumption. The series of experimental work using CNC machining center was conducted to validate the proposed energy model. The result shows that the energy efficiency can be improved by optimizing the machining configuration.

In contrast, Ahmad A. et al[16] observed the specific cutting energy, tool wear and surface quality in response to the cutting parameters such feed rate, cutting speed and depth of cut during cutting of grade 3 titanium alloy. The experimental work was optimized using Taguchi L9 orthogonal array and analysis found that the cutting speed had the most influential ration for specific machining energy while surface roughness was greatly influenced by the cutting feed rate. The empirical machining energy model was established and validated with experimental work and was found to be highly accurate.

Another approach in optimizing machining energy consumption is by developing the energy model based on the machine NC program. The detail of energy consumption for machining activities was analyzed and popularized into energy model. The genetic and ant colony algorithm was able to optimize the energy model by minimizing the non-value-added machining activities such air-cutting and tool rapid movement. The verification using case studies revealed that the model was 95.3% accurate as compared to actual machining energy usage [17]. This energy prediction model is able to guide the machinist and industries in meeting the sustainable manufacturing objective.

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To better visualize machining energy, the Virtual Machining Energy Toolkit (V_MET) was developed to simulate the power usage of during CNC milling cutting operation based on the part G-code program. The milling operations observed were various cutting parameters, NC operation and repasses over previously cut regions. The toolkit provided good accuracy of energy consumption with 4.3% error in total energy and Mean Average Percentage Error (MAPE) of 5.6% which has been validated by the experimental cutting trials [18] [19].

The cutting energy in machining process is governed by machining parameter and machining condition. In milling for example, the main parameters are spindle speed, feed rate and depth of cut, while machining conditions are such as cutting type (eg. Face mill, slot mill, pocketing and etc), wet and dry cut, cutting path and others [20] [21]. Meanwhile, Ke Xu and Kai Tang [22] investigated the influence of feed rate, axial and radial depth of cut on energy consumption during rough milling operation. AR Hemdi et al[23] [24] studied the machining energy of various tool paths, including parallel, morphing spiral, and spiral, and discovered that the feed rate and spindle speed were the significant parameters influencing the energy of machining for all three cutting paths studied. High feed rate increases the material removal rate and reduces the cutting time, which may lower the energy usage. On the other hand, an increase in feed rate will significantly maximize the cutting force, which may then influence the cutting energy [25] [26]. This hypothesis motivates this research to further study the energy behavior during machining process.

## 2.0 METHODOLOGY

Face milling of the Aluminum 6061 block with an HSS endmill tool was used in the experimental work to investigate energy consumption during machining. The design of experiment (DoE) approach using Response Surface Methodology (RSM) was used to optimize the physical experimental work. Following that, the ANOVA analysis yielded the interaction result concerning the machining parameter and the consumption of machining energy.

### 2.1 Machining Parameter

The variable machining parameters in this research are feed rate, spindle speed, and depth of cut as listed in Table 1. The selected range of parameters is based on the work material of aluminum and high-speed steel end mill cutter, according to the machining handbook. The control parameters of work piece size, tool size, and cutting path, on the other hand, must be constant, as described in Table 2, and the zig-zag path is depicted in Figure 2.

**Table 1**: The range of milling cutting parameter.

| Milling parameter | Range | | |
|---|---|---|---|
| | Low | Medium | High |
| Spindle speed (rpm) | 2000 | 2500 | 3000 |
| Feed rate (mm/min) | 100 | 200 | 300 |
| Depth of cut (mm) | 0.25 | 0.5 | 0.75 |

**Table 2:** The machining control parameter.

| Type of parameters | Values/control parameter |
|---|---|
| Cutting tool size | 3 flute, 10mm HSS end mill |
| Workpiece face mill area | 40mm x 40mm Al 6061 |
| Cutting path | Zig-zag |
| Cutting condition | Dry cut |


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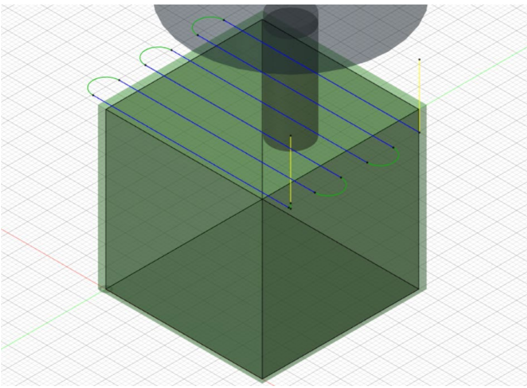

**Figure 2:** A zig-zag cutting path for face mill operation

## 2.2 Response Surface Methodology (RSM)

Response Surface Methodology (RSM) provides tabular data or the number of trials required on a CNC milling machine to obtain reliable data for the following phase. The cutting parameters are used as a reference to obtain the data generated by the Response Surface Methodology (RSM). There are a total of twenty tests that must be carried out. The Box Behnken approach with Central Composite Design (CCD) for three input factors (spindle speed, depth of cut, feed rate) and three

**Table 3.** The list of experimental work consists of different combinations of cutting parameter.

| Run | Spindle speed, rpm | Feed rate, mm/min | Depth of cut, mm |
|---|---|---|---|
| 1 | 2000 | 300 | 0.5 |
| 2 | 2500 | 200 | 0.5 |
| 3 | 2500 | 200 | 0.5 |
| 4 | 2500 | 200 | 0.5 |
| 5 | 2500 | 200 | 0.5 |
| 6 | 2500 | 200 | 0.5 |
| 7 | 3000 | 200 | 0.75 |
| 8 | 3000 | 300 | 0.5 |
| 9 | 2000 | 200 | 0.75 |
| 10 | 3000 | 200 | 0.25 |
| 11 | 2500 | 100 | 0.75 |
| 12 | 3000 | 100 | 0.5 |
| 13 | 2000 | 100 | 0.5 |
| 14 | 2500 | 100 | 0.25 |
| 15 | 2500 | 200 | 0.5 |
| 16 | 2500 | 200 | 0.5 |
| 17 | 2000 | 200 | 0.25 |
| 18 | 2500 | 200 | 0.5 |
| 19 | 2500 | 300 | 0.25 |
| 20 | 2500 | 300 | 0.75 |

The power usage and machining time of each face mill operation were recorded and machining electrical energy can be determined using Equation 2 and area under the power versus time graph. The RSM visualizes interactions between parameters and energy using surface plot, while the analysis of variance, ANOVA evaluates the significant factor and regression model of machining energy.

## 2.3 Equipment

The 3-axis CNC desktop milling machine was used to face mill the 40mm x 40mm surface of Aluminum 6061 work material using 3 flutes, 10mm diameter of end mill cutter as shown in

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Figure 3 and Figure 4. Meanwhile, the power usage and machining time were measured and recorded using Fluke Power Analyzer as in Figure 5.


**Figure 3**: 3-axis CNC desktop

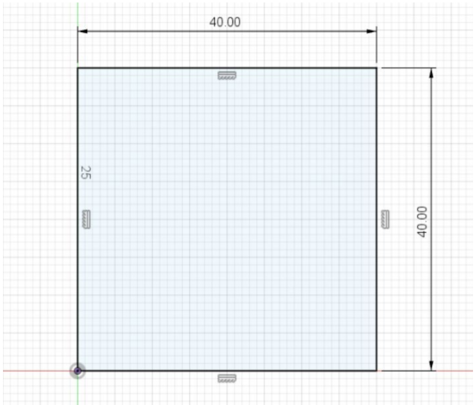


**Figure 4**: Surface area of work piece size of Aluminum 6061

**Figure 5**: Fluke power analyzer

## 3.0 RESULTS AND DISCUSSION

### 3.1 Machining Energyfont 11

The power usage and machining time during face mill cutting for 1st cutting of 2000 rpm spindle speed, 300mm/min feed rate, 0.5mm depth of cut milling parameters are presented in power versus time plot as in Figure 6. The power usage trend can be divided into 2 sections which are power during non-cutting operation or machine power during idle condition and power during


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cutting operation. Power usage during cutting operation is higher than non-cutting power because it was utilized to rotate the spindle and other machine components to cut the work material and overcome the high frictional and cutting force.

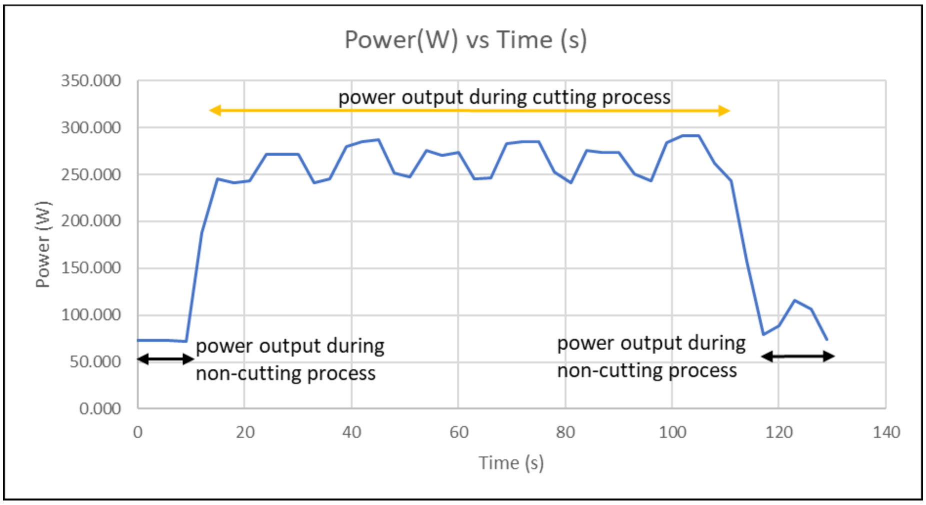


**Figure 6**: Power output during machining operation consists of non-cutting and cutting processes.

The average power consumption during cutting process can be determined by the best fit line across the machining time as shown in Figure 7. Then, the cutting energy is determined by the area under the graph of power versus time which can be calculated by the integration of best fit line as the sample calculation below:

$$P = 0.1329t + 258.17$$

$$= \int_0^{96} \frac{0.1328}{2} t^2 + 258.17t$$
$$= 25396.7232 \text{ J}$$

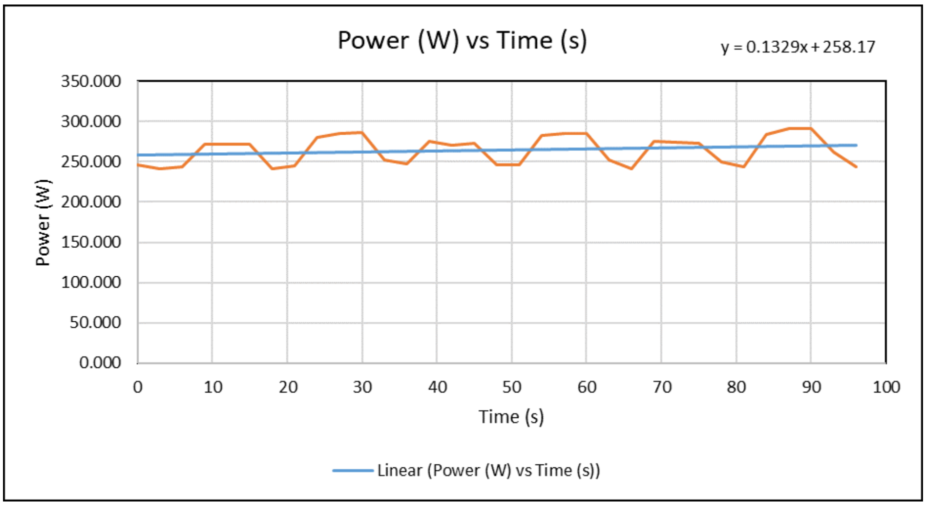


**Figure 7**: The power usage during cutting operation

The cutting power versus machining time for each 20 cutting operations were plotted and the average cutting energy was calculated by the area under the graph. The cutting energy for each 20 cutting operations is listed in Table 4.

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**Table 4**: Experimental result

| No | Spindle speed (rpm) | Feed rate (mm/min) | Depth of cut (mm) | Energy (J) |
|---|---|---|---|---|
| 1 | 2000 | 300 | 0.5 | 12593.497 |
| 2 | 2500 | 200 | 0.5 | 24964.339 |
| 3 | 2500 | 200 | 0.5 | 25343.501 |
| 4 | 2500 | 200 | 0.5 | 19293.636 |
| 5 | 2500 | 200 | 0.5 | 25396.723 |
| 6 | 2500 | 200 | 0.5 | 24739.814 |
| 7 | 3000 | 200 | 0.75 | 24998.016 |
| 8 | 3000 | 300 | 0.5 | 29808.367 |
| 9 | 2000 | 200 | 0.75 | 26246.024 |
| 10 | 3000 | 200 | 0.25 | 26937.278 |
| 11 | 2500 | 100 | 0.75 | 50884.774 |
| 12 | 3000 | 100 | 0.5 | 20593.920 |
| 13 | 2000 | 100 | 0.5 | 50183.440 |
| 14 | 2500 | 100 | 0.25 | 43905.067 |
| 15 | 2500 | 200 | 0.5 | 23278.464 |
| 16 | 2500 | 200 | 0.5 | 19554.317 |
| 17 | 2000 | 200 | 0.25 | 25535.539 |
| 18 | 2500 | 200 | 0.5 | 25092.775 |
| 19 | 2500 | 300 | 0.25 | 26245.281 |
| 20 | 2500 | 300 | 0.75 | 19291.125 |

### 3.2 Interaction between Spindle Speed, Feed Rate, Depth of Cut and Cutting Energy

The interaction between feed rate, spindle speed and energy is visualized using 3D surface plot and contour plot as shown in Figures 8 to Figure 13. According to Figure 8 and Figure 9, the high cutting energy occurs at low spindle speed and low feed rate. Meanwhile, the lowest cutting energy can be obtained at high feed rate and low spindle rotational speed. In addition, there is not much difference in cutting energy by changing the depth of cut and spindle rotational speed as

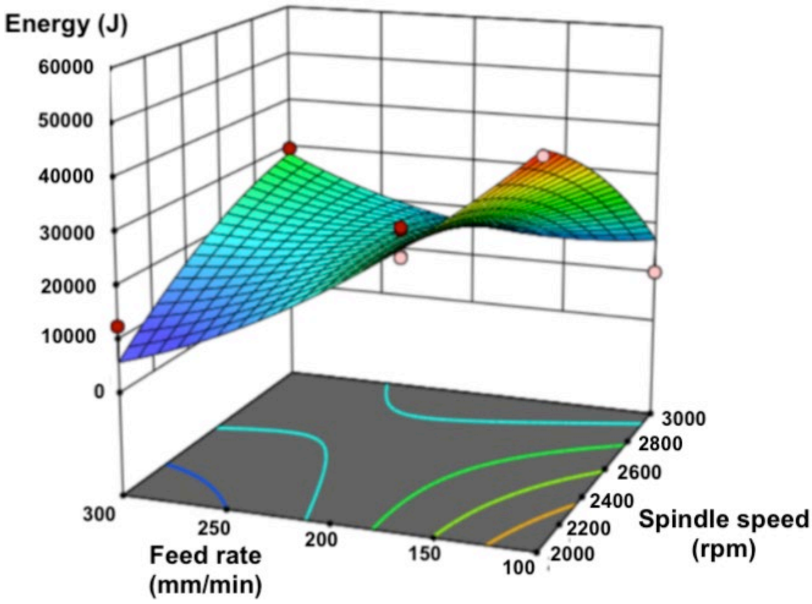


**Figure 8**: The 3-D surface plot of spindle speed, feed rate and energy.

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indicated by Figure 10 and Figure 11. Furthermore, Figure 12 and Figure 13 illustrate the interaction between feed rate and depth of cut which indicates that high cutting energy occurs at low feed and high depth of cut. Meanwhile, the lowest energy can be achieved by minimizing the feed rate and increasing the depth of cut.

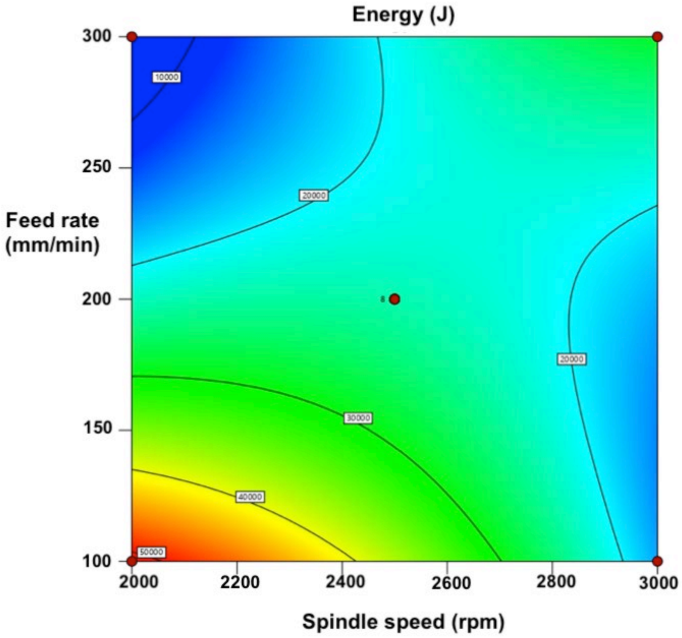


**Figure 9**: The contour plot of spindle speed, feed rate and energy interaction.

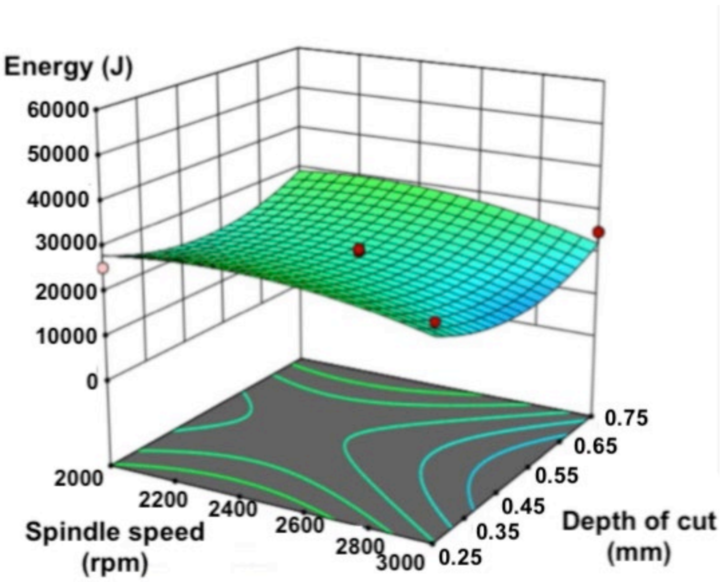


**Figure 10**: The 3-D surface plot of spindle speed, depth of cut and energy.

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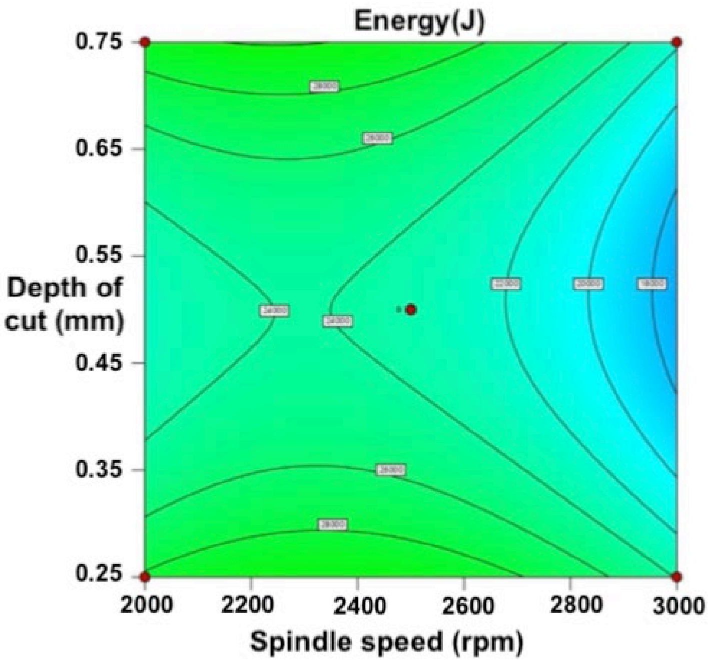


**Figure 11**: The contour plot of spindle speed, depth of cut and energy interaction.

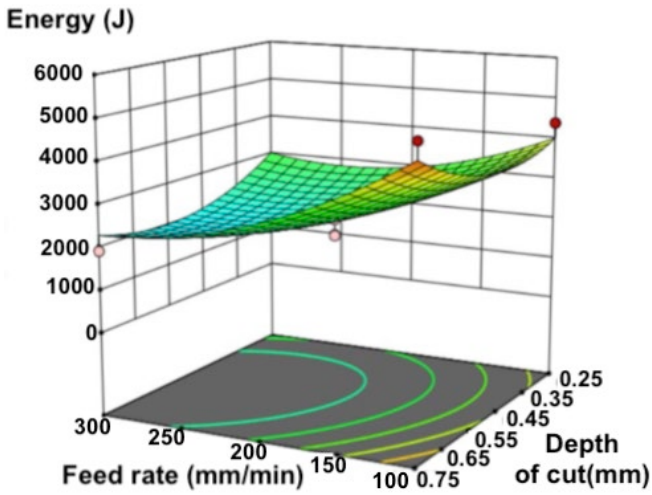


**Figure 12**: The 3-D surface plot of feed rate, depth of cut and energy


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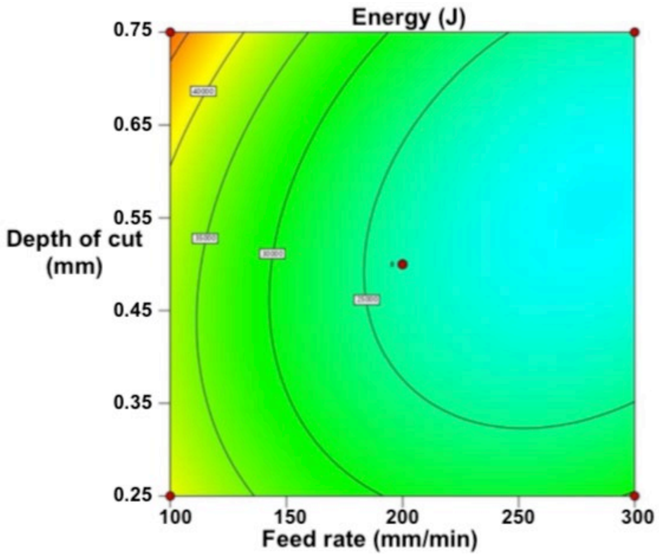


**Figure 13**: The contour plot of feed rate, depth of cut and energy

### 3.3 ANOVA Analysis

Table 5 shows the ANOVA analysis result, which shows that the analysis model is significant with a P-value of 0.0011 (the P-Value must less than 0.05 to be significant). The feed rate, speed x feed rate, (Feed rate)², and (Depth of cut)² are significant with P-values of 0.0006, 0.0002, 0.0314 and 0.0258 respectively. Meanwhile, the lack of fit value is only 0.0073, which implies that there was only a 0.73% chance that a lack of fit could occur.

The feed rate P-Values model has a value of 0.006 which indicates that the feed rate has the most impact on milling cutting energy. In contrast, the high P-value (greater the 0.05) for spindle speed and depth of cut determine that these two parameters have less influence on the milling cutting energy. In addition, for the two-way interaction, the combined parameter of feed rate and spindle speed will greatly influence the milling cutting energy.

**Table 5**: ANOVA Analysis

| Source | Sum of Squares | df | Mean Square | F-value | p-value | |
|---|---|---|---|---|---|---|
| **Model** | 1.871E+09 | 9 | 2.079E+08 | 8.81 | 0.0011 | significant |
| A-Spindle speed | 6.453E+07 | 1 | 6.453E+07 | 2.73 | 0.1293 | |
| B-Feed Rate | 5.633E+08 | 1 | 5.633E+08 | 23.86 | **0.0006** | significant |
| C-Depth of Cut | 1.810E+05 | 1 | 1.810E+05 | 0.0077 | 0.9320 | |
| AB | 8.210E+08 | 1 | 8.210E+08 | 34.78 | **0.0002** | significant |
| AC | 1.755E+06 | 1 | 1.755E+06 | 0.0744 | 0.7906 | |
| BC | 4.854E+07 | 1 | 4.854E+07 | 2.06 | 0.1821 | |
| $A^2$ | 5.505E+07 | 1 | 5.505E+07 | 2.33 | 0.1577 | |
| $B^2$ | 1.476E+08 | 1 | 1.476E+08 | 6.25 | **0.0314** | significant |
| $C^2$ | 1.614E+08 | 1 | 1.614E+08 | 6.84 | **0.0258** | significant |
| **Residual** | 2.361E+08 | 10 | 2.361E+07 | | | |
| Lack of Fit | 1.896E+08 | 3 | 6.319E+07 | 9.51 | 0.0073 | |
| Pure Error | 4.651E+07 | 7 | 6.644E+06 | | | |
| **Cor Total** | 2.107E+09 | 19 | | | | |


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### 3.4 Machining Energy Model

Based on the experimental data, the regression equation for machining energy was generated using RSM and is expressed in Equation (3).

$$\begin{aligned}\text{Energy, } J = {} & 1.37183\text{E}+05 + 9.07010\, N - 957.83156\, f - 54549.56720\, d + 0.286522\, N{*}f \\ & -5.29949\, N{*}d - 139.33863\, f{*}d - 0.013881\, N^2 + 0.568209\, f^2 + 95064.40900\, d^2 \end{aligned} \tag{3}$$

Where:

$N$ = spindle speed
$f$ = feed rate
$d$ = depth of cut

Table 6 shows the model fit summary for energy model as defined in Equation (3). The reliability, $R^2$ value is 0.8880 which specifies that the model generated is 88% reliable. Meanwhile, Adeq Precision measures the signal-to-noise ratio. A ratio larger than 4 is preferred showing that the noise ratio is at minimum value. The signal-to-noise ratio of 13.225 (higher than 4) suggests a sufficient signal that the noise ratio is at a minimum value. This indicates that the proposed model can be used for prediction of milling cutting energy.

**Table 6**: Model fit summary for energy model

| Reliability, R | Value |
|---|---|
| $R^2$ | 0.8880 |
| Adjusted $R^2$ | 0.7871 |
| Predicted $R^2$ | -0.4683 |
| Adeq Precision | 13.2245 |

## 4.0 CONCLUSION

In the cutting of Aluminum using HSS cutting tool, the feed rate was identified as the most influential factor for determining energy consumption during milling cutting operation; the lower the feed rate, the higher the energy value used. Meanwhile, spindle speed and depth of cut have less of an impact on cutting energy consumption, and at the same time, the depth of incision has a negligible impact on energy consumption. Moreover, RSM was able to generate the 3D surface plot which help visualize the influence of cutting parameter to the cutting energy behavior. Furthermore, the ANOVA analysis provides an energy model with an 88% reliability, which can then be used for energy prediction for milling cutting operations.

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