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The Efficiency Performance of CNC Milling Machine with Vibration Sensor

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Abstract

This study evaluates the operational effectiveness and surface finish quality of a CNC milling machine equipped with a real-time vibration monitoring system. By integrating a vibration sensor into the milling setup, variations in machine behaviour under different cutting parameters were analysed to identify factors contributing to excessive tool wear, chatter, and increased surface roughness. The vibration data provided early detection of inefficiencies and potential faults, offering valuable insights into the dynamic stability of the milling process. The findings indicate that vibration analysis is a reliable method for optimising cutting conditions, enhancing process control, and improving the overall precision and productivity of CNC milling operations.

1. Introduction

Aluminium 6061's high strength, corrosion resistance, and functionality make it an effective alloy in industry. Since it is mostly made of silicon, magnesium, and aluminium, it may be used for a variety of things, such as structural frames, automobile parts, marine fittings, and aerospace components. It is a common option for both extruded and rolled product shapes due to its good machinability and weldability as well as its capacity to be heat-treated for improved mechanical qualities. Furthermore, aluminium 6061 continues to perform well in challenging conditions, further enhancing its adaptability in the production of consumer and industrial products. The author [1] analysed the several approaches and techniques that researchers have used to identify the vibration that affected surface roughness throughout the milling process.

1.1 Vibration Analysis

An essential monitoring and predictive maintenance tool for CNC milling machines, vibration analysis evaluates the dynamic behaviour of machine parts in use. The method allows for the detection of mechanical problems such as spindle imbalance, tool wear, misalignment, structural looseness, and bearing faults by using sensors like accelerometers to record vibration signals. Understanding the origin and intensity of vibrations through the frequency analysis of the spectrum and time-domain signal interpretation enables quick action to stop equipment failure [2]. In precision manufacturing settings, vibration analysis improves machining accuracy, increases tool and machine life, reduces unplanned downtime, and contributes in overall process optimization [3].

1.2 Surface Roughness

An important machining parameter that has a direct impact on a manufactured part's performance, appearance, and usefulness is surface roughness. It describes the tiny imperfections on a machined surface that are frequently brought on by vibration, tool movement, material characteristics, and cutting parameters including feed rate, speed, and depth of cut. Maintaining the ideal surface roughness in precision manufacturing is essential for ensuring component fit, fatigue strength, and wear resistance [4]. Surface roughness analysis gives producers important information about the stability of the machining process and the state of the tool, allowing them to modify settings for higher quality. Monitoring and forecasting surface roughness using sensor data, such as vibration levels, has become crucial to attaining reliable and effective machining performance as companies embrace smart manufacturing processes.

2.0 Methodology

Discover every important variable that will have a significant impact on the workpiece's surface roughness when compared to the spindle housing's vibration. After that, all of the data will be specified into the RSM experiment design. We will gather sets of various parameters and the experiment will be conducted using all of those results. The Mitutoyo SJ-410 surface roughness tester will be used to assess each workpiece's roughed surface in order to determine the average surface roughness, or Ra. The RSM method will be used to analyze this data.

2.1 Experimentation

The experiment used a 50 x 50 mm piece of aluminum 6061 material, and the input parameters taken into consideration are feed rate, constant cutting speed, and various cut depths, as indicated in Table 1. The face milling process was carried out using a carbide cutter with a 10mm diameter that operates in a zigzag pattern. The machine program sets up the machining operation to obtain the precise coordinates for the machine.

Table 1 *Experiment data tabulation*

SI. No	Cutting speed (m/min)	Feed rate (mm/rev)	Depths of cut (mm)
1	35	0.1	0.2
2	35	0.1	0.4
3	35	0.1	0.6
4	35	0.1	0.8
5	40	0.1	0.2
6	40	0.1	0.4
7	40	0.1	0.6
8	40	0.1	0.8
9	45	0.1	0.2
10	45	0.1	0.4

11	45	0.1	0.6
12	45	0.1	0.8
13	50	0.1	0.2
14	50	0.1	0.4
15	50	0.1	0.6
16	50	0.1	0.8

2.2 CNC milling simulation

CNC is a technique for controlling and automating industrial equipment movements. CNC milling is a type of machining where multi-point rotating cutting tools are moved and operated by computerized controls [5]. To achieve the desired shape and size, excess material is progressively removed from the workpiece as the tools rotate and move across its surface. The facing operation was pursued based on the CNC milling machine's NC stored program. Following face machining on a CNC machine operating at a constant spindle speed of 1430 rpm, a feed rate of 0.1 mm/rev, and adjusting the depth of cut, Figure 1 shows the surface roughness of the workpiece feature.

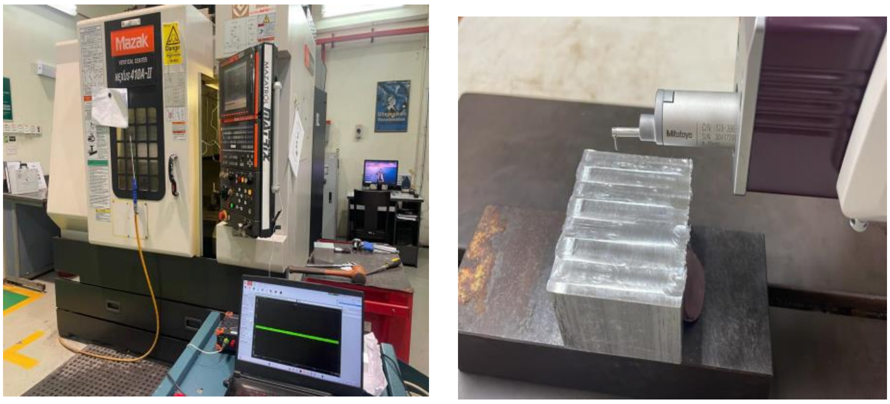
0.2 mm, 0.4mm, 0.6mm, and 0.8mm, due to the chatter impulse at varied cutting depths. As the odd pattern emerged, considerable chatter was produced, resulting in peak vibration. The experimental measurements of average roughness (Ra) at different depths were determined to be 0.308 µm , 0.315 µm, 0.335 µm, 0.358 µm, respectively. The experimental value of 0.2, 0.4, 0.6, and 0.8 mm of the face milling job resulted in the cut and feed rate parameters and surface roughness phenomenon being proportional [1].

2.3 Experimental Details

The Mazatrol milling machine with a 4-tooth tungsten carbide end mill cutter was used for the experiments. The workpiece measures 50 mm by 50 mm by 28 mm and is made of an aluminum alloy (Al6061).

The procedure of the experimental setup is as stated as below:

1. Turn on the vertical CNC milling machine to ensure the machine is ready to perform.
2. Prepare the 50mm x 50mm x 28mm rectangular aluminium block for the setup of the machining process for CNC end milling.
3. The 4-tooth tungsten carbide end mill cutter with a diameter of 10mm is used. There is 1 constant parameter that will be used to run all 16 experiments, which is the feed rate of 0.1m/min.
4. All the created code file is set up in the Mazatrol CNC Milling Machine to perform all the milling operations.
5. The 16 experiments will be conducted under dry conditions with different parameters of the milling process which are cutting speed of 35m/min, 40m/min, 45m/min and 50m/min and depth of cut of 0.2mm, 0.4mm, 0.6mm and 0.8mm.
6. The roughness of surface of the workpiece will be measured 5 times using the surface roughness tester (Mitutoyo SJ-410) to obtain the average value of surface roughness, Ra



(a) (b)

Fig. 1 *(a) CNC milling machine with vibration sensor; (b)Surface roughness tester*

3.Results and Discussion

Predicting the average surface roughness of the milled surface block's centre is the aim of this research. To determine how the cutting settings affect the average roughness. The outcomes of the experiment were imported into Microsoft Excel. Surface roughness is one of the output responses from the data collecting.

Table 2 *Experimental data of vibration levels and surface roughness*

SI. No	Cutting speed (m/min)	Feed rate (mm/rev)	Depths of cut (mm)	Vibration levels, a (m/s^2)	Surface roughness, Ra (μm)
1	35	0.1	0.2	12400	0.308
2	35	0.1	0.4	17757	0.315
3	35	0.1	0.6	18352	0.316
4	35	0.1	0.8	18639	0.321
5	40	0.1	0.2	18517	0.324
6	40	0.1	0.4	18842	0.332
7	40	0.1	0.6	19032	0.335
8	40	0.1	0.8	19229	0.343
9	45	0.1	0.2	20980	0.347
10	45	0.1	0.4	21150	0.351
11	45	0.1	0.6	22100	0.352

12	45	0.1	0.8	23158	0.352
13	50	0.1	0.2	23553	0.358
14	50	0.1	0.4	23890	0.362
15	50	0.1	0.6	24132	0.365
16	50	0.1	0.8	25780	0.370

3.1 Regression Models

The regression equation for the surface roughness based on the cutting parameter as below:

$$R_a = 0.192 + 0.003 \times V_c + 0.019 \times a_p$$

The "Predicted Roughness vs. Measured Roughness" graph in Figure 2 demonstrates a robust linear relationship between the actual measured values from experiments and the anticipated surface roughness values produced by the regression model. Since the slope and intercept of the line of best fit, which is represented by the equation y = 0.9837x + 0.0055, are both close to 1, the model is said to closely approach the measured data. This implies that the prediction model can estimate surface roughness with little variation from the actual values and is quite accurate.

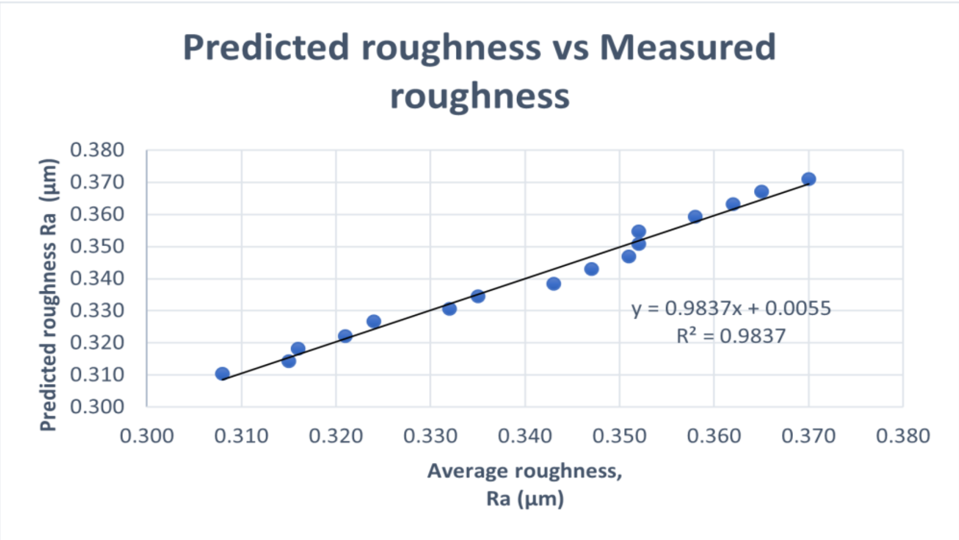


Fig. 2 *Graph of predicted roughness and measured roughness*

In addition, an excellent fit is demonstrated by the coefficient of determination (R2 = 0.9837), which indicates that the measured data account for 98.37% of the variability in the projected surface roughness. The model's trustworthiness is further supported by the data points' tight clustering around the regression line and the absence of any notable outliers. This excellent prediction accuracy confirms the incorporation of smart sensor technology in CNC milling processes and supports the use of cutting parameters and vibration data in surface quality prediction.

3.1 Validation of the Models

As indicated in Table 3, the model was validated by comparing the measured results for different cutting settings with the predicted surface roughness values. The prediction errors of the regression model ranged from 2.33% to 10.71%, indicating high accuracy. In the majority of cases, the projected value of 0.301 μm was marginally different from the actual 0.308 μm, and in one case, the measured roughness of 0.308 μm was exactly expected to be 0.308 μm. These little variations show that the model accurately predicts surface roughness depending on input parameters such as vibration levels, cutting speed, and depth of cut. The model's durability is confirmed by the very low percentage errors across trials, which makes it appropriate for use in real-time quality of surfaces prediction in CNC milling operations.

Table 3 *Details of the cutting parameters, measured surface roughness and predicted values for model validation*

Cutting speed (m/min)	Depths of cut (mm)	Vibration levels, a (m/s^2)	Measured roughness, Ra (μm)	Predicted value, Ra (μm)	Error (%)
35	0.2	12400	0.308	0.301	2.33
35	0.4	15870	0.315	0.305	3.28
35	0.6	18100	0.341	0.308	10.71
40	0.2	18517	0.324	0.316	2.53
45	0.2	20980	0.347	0.331	4.83

4. Conclusion

In conclusion, this study effectively illustrated how, particularly in the overall setting of the Industry 4.0 movement, putting a vibration sensor system into a CNC milling machine may greatly increase its operational efficiency. By examining the relationship between spindle vibration and surface roughness across various cutting parameters, the study provided important insights into how to optimize machining conditions to enhance machine health and surface quality. Predictive diagnostics was made possible by the sensor-based monitoring strategy and regression models that were built, which reduced downtime and enhanced manufacturing consistency. In the conclusion, this study emphasizes the importance of equipping old CNC machines with intelligent sensing technologies in order to facilitate data-driven manufacturing and increase the machines' useful life in contemporary industrial settings.

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