Taguchi-Based Six Sigma Approach to Optimize Surface Roughness for Milling Processes

Sky Chou, Joseph C. Chen

***Abstract*—**This paper focuses on using Six Sigma methodologies to improve the surface roughness of a manufactured part produced by the CNC milling machine. It presents a case study where the surface roughness of milled aluminum is required to reduce or eliminate defects and to improve the process capability index C_p and C_{pk} for a CNC milling process. The six sigma methodology, DMAIC (design, measure, analyze, improve, and control) approach, was applied in this study to improve the process, reduce defects, and ultimately reduce costs. The Taguchi-based six sigma approach was applied to identify the optimized processing parameters that led to the targeted surface roughness specified by our customer. A L_9 orthogonal array was applied in the Taguchi experimental design, with four controllable factors and one non-controllable/noise factor. The four controllable factors identified consist of feed rate, depth of cut, spindle speed, and surface roughness. The noise factor is the difference between the old cutting tool and the new cutting tool. The confirmation run with the optimal parameters confirmed that the new parameter settings are correct. The new settings also improved the process capability index. The purpose of this study is that the Taguchi–based six sigma approach can be efficiently used to phase out defects and improve the process capability index of the CNC milling process.

***Keywords*—** CNC machining, Six Sigma, Surface roughness, Taguchi methodology.

I. Introduction

MACHINING can be used to create a variety of features including holes, slots, pockets, flat surfaces, and even complex surface contours [1]. Usually machined parts are metal, but almost any material can be machined, including plastics, composites, and wood. Because of its versatility, machining is often considered the most common and widely used of all manufacturing processes [1]. Throughout the years, machine tool manufacturers have created machines capable of maximizing the utility of all types of cutting tools, while lubricant manufacturers have developed new coolants and lubricants to allow increased rates of metal removal.

Accompanying the improvements of machines, the invention of the computer allowed for the development of computer numerically controlled (CNC) machines which greatly improved the manufacturing industry by vastly increasing output per employee. CNC machining allows employees to setup cutting parameters easily and change tools quickly. Out of all the machining processes, milling is the most common form of machining [1]. Milling is a machining process that rotates the cutting tool at high speeds to remove material from a workpiece. Milling is generally used to manufacture parts that are not situated on the same axis and have several different features, such as holes, slots, pockets, and surface contours. Milling is also commonly used as a secondary process to continue or perfect features on parts that were produced using a different manufacturing process [1]. Although milling can be done to raw materials, because of the high tolerances and surface finishes that it can offer, it is the best process for adding precise features to a part whose main shape has already been formed [1].

Even with all the improvements made with milling machines, the problem of maintaining surface roughness within specifications still exist [2]. The surface inconsistencies of a material can be affected by a wide range of factors such as vibration during machining, the quality of the tool used, and the quality of the machined material. It can also be affected by cutting parameters as spindle speed, feed rate, depth of cut and types of coolant used [3]. These surface inconsistencies have a major impact on the quality and on the performance of the end product, regardless of shape and size [2]. Therefore, the management of these surface inconsistencies is necessary to maintain high product performance [3].

Along with improving the process, finding the optimum parameters to eliminate the most waste is very important [6]. To do this, a number of statistical models have been developed for the analysis and optimization of machining parameters such as response surface methodology (RSM), regression techniques, analysis of variance (ANOVA), and the Taguchi method [6]. The Taguchi-based optimization technique has produced a unique and powerful optimization discipline that differs from traditional practices. The Taguchi methods provide an effective and standardized way to optimize designs for overall performance and quality, as well as cost [6]. Typical experimental design methods are usually very difficult to use because of the extensive amount of experimental works that have to be performed when the number of the process parameters increase [3]. In order to deal with this problem, the Taguchi method has developed a specific design of orthogonal arrays to study all the process parameters with only a small number of experimental works.

II. Problem Statement

In this case study, our customer has tightened the surface roughness specifications in order to improve overall part quality. Our products had no problem meeting the old surface roughness specifications of 50 ± 20 µin. However, with the new specifications of 45 ± 15µin, most of our products have

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become defective parts. The process capability C_p and process capability index C_{pk} are .34 and .25 respectively. The goal of this case study is to make the C_p greater than 1.33 and C_{pk} greater than 1. To achieve this goal, we need to revise the milling process to produce parts with improved surface roughness quality. Therefore, we will be implementing the DMAIC approach coupled with the Taguchi method. Fig. 1 shows the flowchart that illustrates the whole process of this case study.

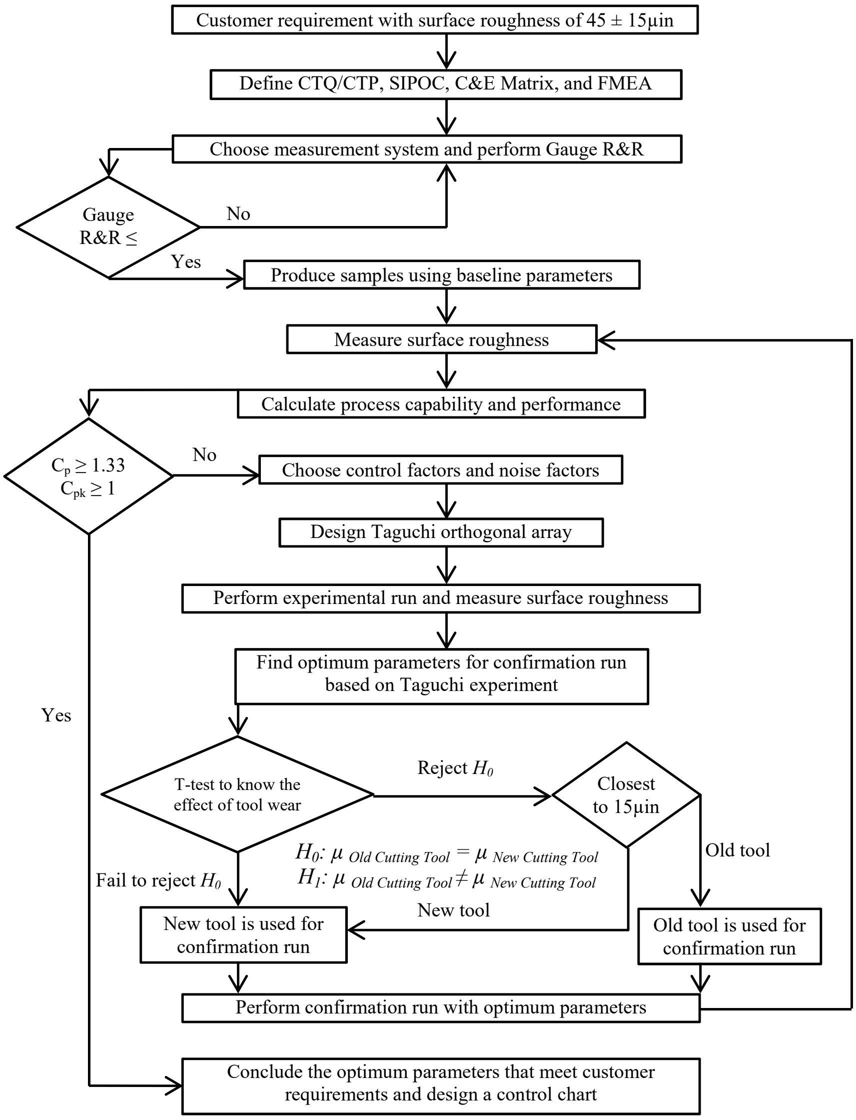

Fig. 1 Six Sigma process flowchart for milling

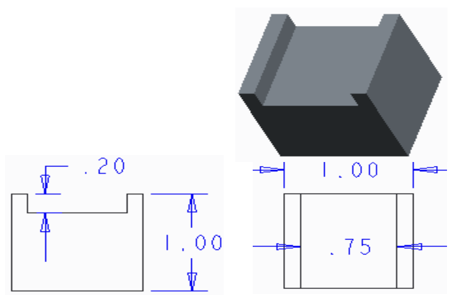

Fig. 2 Creo model of specimen part and dimensions

III. Experimental Procedure

In order to obtain required surface roughness while reducing cost, finding the best fit process improvement methodology is essential. Among some of the methods include Six Sigma, Re-engineering, Total Quality Management (TQM), Just-In-Time (JIT), and Poka-Yoke [4]. Re-engineering, JIT, and poka-yoke are all tools that can be used within TQM or Six Sigma. Six Sigma includes all tools and philosophies of TQM but also has more advanced statistical tools and incorporating these tools creates the opportunities for bigger and better improvements, and improvements that might not have been found with just TQM [4]. The goal of the Six Sigma methodology is to improve part quality by identifying and removing the causes of defects and minimizing variability in manufacturing processes [5]. Six Sigma projects follow the DMAIC approach. We first define the problem, measure the performance, analyze and identify root causes. Then we improve the results based on analysis and control the improved process.

A. Define

The define stage is the first stage of this project. In this stage, the six sigma team made a 3D model in Creo Parametric 2.0, shown in Fig. 2, of the required part based on the customer's specification of a 1 in cube with 0.75 in wide and 0.2 in depth cut. This includes a surface roughness within the tolerance of 45+/-15µin on the machined surface. After this, we brainstormed root causes with a fishbone diagram and then we use a CT (critical to) Tree to further identify the problem and the processes that need to be improved in this case study.

The key parameters that could affect the surface roughness were listed and analyzed using the fishbone diagram, the potential failure modes were also determined. Fig. 3 shows a fishbone diagram developed based on the various processes involved. It was classified into six classifications: People, Method, Measurement, Machine, Environment, and Materials and a total of 17 possible root causes that might be related to getting a high surface roughness of the machined surface.

With the potential causes identified, we can use a CT (critical to) tree to convert customer needs to measureable performance requirements. A CT tree is a tool that relates the needs that are considered important by the customer into the product and service characteristics and links these characteristics to organizational processes [8]. These help in knowing what our customers are looking for and the steps to take to ensure product quality. Key characteristics and important product parameters are defined in terms of quality, customer, and process and rated against each other. Table I shows the characteristics against each other. The CTQ (critical to quality) vs. CTP (critical to process) were compared to the process by a ranking following scale 1, 4 and 9. If a particular process has a high impact on quality, it was ranked 9, the medium impact was ranked with 4, the insignificant impact was ranked 1, and the ones with no impact was left blank.

B. Measure

In the measure phase, the focus was on the measurement system and gathering root causes of the high surface roughness of the manufactured part. We decided to use the Zegage 3D optical profiler to measure our surface roughness because the Zegage machine provides fast and accurate surface roughness readings without contacting the part. With our measurement system determined, we can conduct our gage R&R study. A gage repeatability and reproducibility (gage R&R) study was conducted by measuring the surface roughness of nine parts cut from the baseline parameters. The gage R&R study was performed using three appraisers and three trials for each of the nine parts, and the value were recorded. The results show the surface roughness average of the nine parts to be 53.09 µin with an equipment variation 70.66 percent and an appraiser variation of -44.50 percent resulting in an overall 83.50 percent gage R&R. This value of 83.50 percent is high as compared with the acceptable range of 30 percent, and this indicates there is a need for improvement of the process; therefore, we need to determine our key parameter input variables.

TABLE I
CRITICAL TO PROCESS VS CRITICAL TO QUALITY TREE

	Surface roughness	Delivery date	Manufacturing cost	Quantity & right product	Selling price
Product design	9		4	9	9
Material cost			9	9	9
Processing cost		4	9	1	9
Delivery cost		9	9	1	9
Packaging		9	9	9	9
Order processing		9		9	
Order check		9		9	
Inventory		4	9	9	
Feed rate	9		9	9	
Spindle speed	9		9	4	4
Coolant	9		9	4	1
Depth of cut	9		9	4	

TABLE II
FAILURE MODE AND EFFECT ANALYSIS TABLE OF THE MILLING PROCESS

Process Step/Input	Potential Failure Mode	Potential Failure Effects	SEV	Potential Causes	OCC	Current Controls	DET	RPN
Milling Operation	Wrong depth of cut	Wrong product	7	Wrong program	4	Inspection and quality checks	9	252
	Wrong feed rate	Wrong product	7	Wrong program	4	Inspection and quality checks	9	252
	Wrong spindle speed	High lead time	5	Wrong program	4	Inspection and quality checks	9	180
	Wrong parameters for finish cuts	Wrong product	7	Wrong program	4	Inspection and quality checks	9	252
Part measurement	Wrong program	Wrong specifications	8	Programmer mistake	3	Proper SOP at machine tables	8	192
	Wrong units	Wrong specifications	8	Operator mistake	3	Training	8	192
	Human error	Wrong specifications	8	Noise, vibrations	4	Clean and quite room	6	192
	Mother nature	Wrong specifications	8	Unpredictable	1	None	10	80

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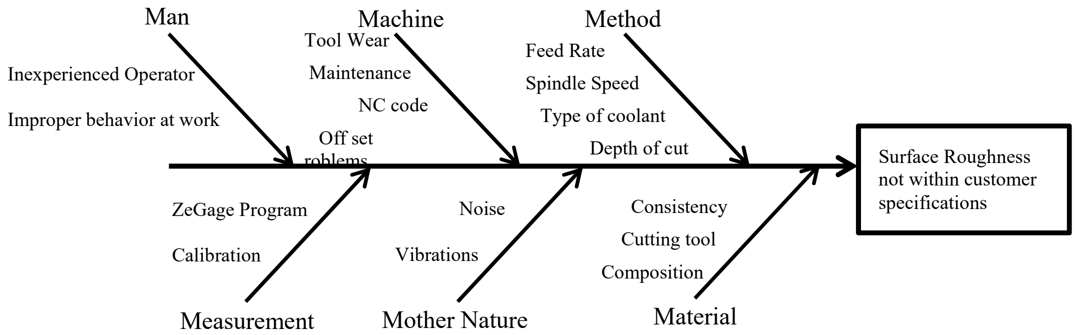

Fig. 3 Fishbone Diagram

A cause-and-effect (C&E) matrix helps us identify which factors affect the outcomes of surface roughness. In the C&E matrix, we multiply the customer importance with rankings and final output number is ranked. With these relationships visible and quantified, we can identify the most influential inputs as key parameters input variables (KPIV). From the C&E matrix, the cutting tool, feed rate (ipm), depth of cut (in), and spindle speed (rpm) are defined as KPIV. The C&E Matrix also provides the initial input to the failure mode and effect analysis.

The next step is to conduct the failure mode and effect analysis (FMEA). The main idea of FMEA is to determine the potential failure modes in the process, as well as their causes and effects. The FMEA of the milling process is shown in Table II. This was done to help identify potential failure modes that could affect the milling process of the aluminum block and the effect of such failures, the risk to customers if these processes fail and how to control them to ensure a better quality product. An FMEA uses three criteria to assess a problem; how severe the problem is, the frequency of the problem, and the detection rate of the problem [9]. The severity is ranked from 1-10 with a low number and high number translating to low impact and high impact respectively. The occurrence is also ranked from 1-10 with a low number meaning that it is not likely to occur and a high number meaning that it is more likely to occur. The detection is ranked from 1-10 with a high number meaning hard detection and a low number meaning easy detection.

TABLE III
MAIN AND NOISE FACTORS TABLE

Designation	Variable	Unit	Levels 1	2	3
A	Feed Rate	Ipm	16	18	20
B	Spindle speed	Rpm	1750	2000	2250
C	Depth of Cut	In	0.04	0.05	0.06
D	Coolant		On	On	Off
	Non- Controllable Factors				
1		Old Cutting Tool			
2		New cutting tool			
Output Variable			Surface roughness		

C. Analyze

A Taguchi experiment was conducted to identify the optimal parameter for the process [7]. This is important because it determines the optimal combination to meet customer specifications. The experimentation will follow Taguchi L_9 orthogonal array to analyze all four parameters. Shown in Table III, the L_9 Taguchi combinations of four main factors, three levels, and one noise factor were used. Our four controllable factors are feed rate (ipm), spindle speed (rpm), finish cut (in), and coolant on or off. Our one uncontrollable factor, or noise factor, is the tool wear. This is represented with an old cutting tool and a new cutting tool.

TABLE IV
TAGUCHI L_9 ORTHOGONAL ARRAY

	Factor				Noise factors			
N	A(Feed)	B(Speed)	C(DOCF)	D(Coolant)	Old cutting tool	New cutting tool	$\bar{Y}$	S/N Ratio
1	1(16)	1(1750)	1(0.04)	1-On	63.98	48.21	56.09	14.03
2	1(16)	2(2000)	2(0.05)	2-On	46.50	42.78	44.64	24.58
3	1(16)	3(2250)	3(0.06)	3-Off	23.60	66.53	45.07	3.43
4	2(18)	1(1750)	2(0.05)	3-Off	25.98	59.18	42.58	5.17
5	2(18)	2(2000)	3(0.06)	1-On	41.76	63.74	52.75	10.61
6	2(18)	3(2250)	1(0.04)	2-On	49.84	49.85	49.84	73.84
7	3(20)	1(1750)	3(0.06)	2-On	57.26	61.63	59.44	25.69
8	3(20)	2(2000)	1(0.04)	3-Off	12.67	58.98	35.83	0.78
9	3(20)	3(2250)	2(0.05)	1-On	51.76	59.62	55.69	20.01

Equation (1), the nominal the better equation, is used to calculate the signal-to-noise ratio. Where η is the response, $\bar{Y}$ is the average of the surface roughness measurements, and s^2 is the variance of the surface roughness data.

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$$\eta = 10log(\frac{\bar{y}^2}{s^2}) \quad (1)$$

A L_9 orthogonal array shown in Table IV is used to organize the parameters affecting the process and the levels at which they are varied.

For the surface roughness, the value in each column that is close to 45 is chosen. For the signal-to-noise (S/N) ratio, the largest value in each column is chosen. The predicted surface roughness, based on the formula $Y_{Predictted} = \bar{Y}_{A2} + \bar{Y}_{B3} + \bar{Y}_{C1} + \bar{Y}_{D2}) - 3\bar{Y}_{all}$, from the first set of parameters $A_2B_2C_1D_3$ is 33.9 µin. The predicted surface roughness from the second set of parameters $A_2B_3C_1D_2$ is 49.8 µin. Since our customer requires surface roughness to be closest to 45 µin, we choose $A_2B_3C_1D_2$ as the optimal setting shown in Table V.

TABLE V
RESPONSE TABLE

	A	B	C	D
Surface roughness				
Level 1	48.60	52.71	*47.25*	54.84
Level 2	*48.39*	*44.41*	47.64	51.31
Level 3	50.32	50.20	52.42	*41.16*
S/N ratio				
Level 1	14.02	14.96	*29.55*	14.89
Level 2	*29.87*	11.99	16.59	*41.37*
Level 3	15.49	*32.43*	13.24	3.13

After finding our optimal settings, we have to conduct hypothesis testing. The hypothesis testing is conducted to see if the tool wear has a significant effect on the surface roughness. A t test is conducted as we compare two means from two sample groups. The hypothesis is shown where $\mu_{\text{Old Cutting Tool}}$ represents the mean of the old cutting and $\mu_{\text{New Cutting Tool}}$ represents the mean of the new cutting tool.

$$H_0: \mu_{\text{Old Cutting Tool}} = \mu_{\text{New Cutting Tool}}$$
$$H_1: \mu_{\text{Old Cutting Tool}} \neq \mu_{\text{New Cutting Tool}}$$

The calculations for the t-test were calculated using (2). Where $\bar{x}_1$ represents the old cutting tool and $\bar{x}_2$ represents the new cutting tool. S^2 is the pooled sample variance and n_1 and n_2 are the sample size [10].

$$t = \frac{\bar{x}_1 - \bar{x}_2}{\sqrt{s^2(\frac{1}{n_1} + \frac{1}{n_2})}} \quad (2)$$

Using 99% confidence interval and a degree of freedom of 16, the t-test value was calculated, and the result was 2.42, with a critical region of -2.58. From the t-test calculations, the test statistic value -2.42 does not fall in the critical region value -2.58, so we fail to reject the null hypothesis. This tells us that there is no significant difference between the old cutting tool and the new cutting tool. Therefore, the new cutting tool will be used to carry out the confirmation runs.

D. Improve

From the Taguchi experimentation, the optimal parameters have been established. Now we can perform a confirmation run to determine if the new parts really have a lower surface roughness than the baseline parts. Eleven parts were cut using the optimal parameters. The confirmation cuts were then measured using the Zegage machine to measure the surface roughness of all the pieces. The results of the confirmation runs are recorded in Table VI.

From the confirmation runs, we can find confidence interval of the process with (3). Where $\bar{x}$ is the average of the conformations runs, t is a critical region, σ is the standard deviation, n is the sample size. By using (3) and considering α=0.01, the experiment is 99% confident the surface roughness will between 42.425 and 47.095 µin.

$$C.I. = \bar{x} \pm t * (\frac{\sigma}{\sqrt{n}}) \quad (3)$$

The average surface roughness for the confirmation cut is 44.76 µin and a standard deviation of 2.44 µin, which is very close to the nominal value 45 µin. We calculated the new C_p and C_{pk} of the process and also plotted a new capability analysis graph in Fig. 4 to see if the process has truly been improved. The new C_p and C_{pk} were calculated to be 2.11 and 2.08 respectively with a standard deviation of 2.44.

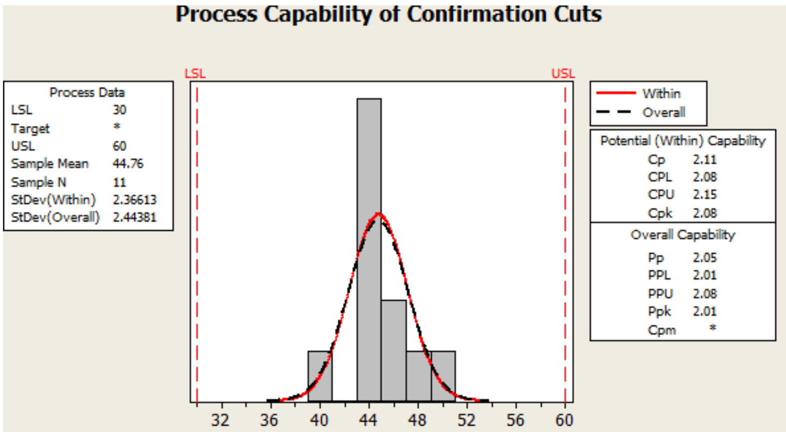

Fig. 4 Process capability graph of optimal parameters

E. Control

Now that we have the optimal parameters confirmed; it is important to keep the process in control. An SPC (statistical process control) chart has been created for the process to ensure no part goes out of the specification limits. The upper control limit (UCL) for X-bar equals 47.7 µin and the lower control limit (LCL) for X-bar equals 41.8 µin. The UCL for R equals 12.4 µin and the LCL equals 0 µin. The process has been improved and is now capable of making the parts meet the customer's desired surface roughness value. It is important to keep this process improved and ensure it doesn't go out of control, to do this a control chart for the X-bar and R-bar was created and is shown in Fig. 5. The UCL, CL, and LCL are shown in blue, red, and green, respectively.

TABLE VI
CONFIRMATION RUNS WITH OPTIMAL PARAMETER SETTINGS

Trial #	1	2	3	4	5	6	7	8	9	10	11	Average
Surface Roughness (µin)	49.53	44.50	46.85	44.81	43.33	40.06	43.52	47.01	43.90	45.07	43.78	44.76

Product:				Manufactured By:							Machine Number:								
Operator Name:				Group ID:							Inspector:								
Date		26-Jun									27-Jun								
Time of Day		8:00 AM	9:00 AM	10:00 AM	11:00 AM	12:00 PM	1:00 PM	2:00 PM	3:00 PM	4:00 PM	8:00 AM	9:00 AM	10:00 AM	11:00 AM	12:00 PM	1:00 PM	2:00 PM	3:00 PM	4:00 PM
Sample Group #		1	2	3	4	5	6	7	8	9	1	2	3	4	5	6	7	8	9
Sample Measurements Value of X	1																		
	2																		
	3																		
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	5																		
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Sum																			
Average $\bar{X}$																			
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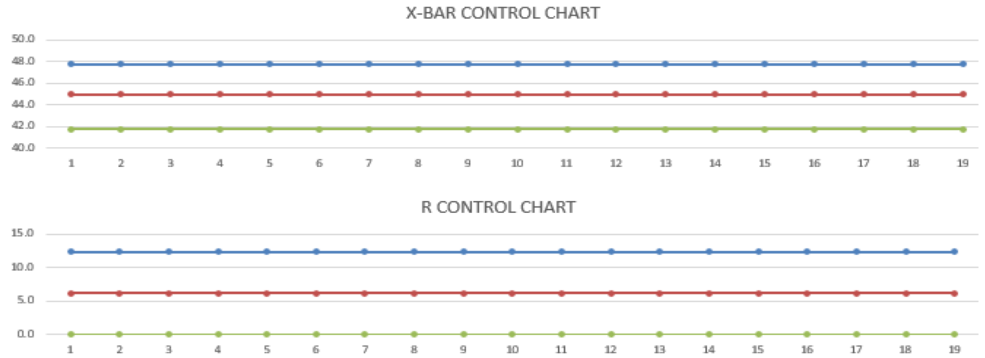

Fig. 5 Statistical process control chart for milling process

IV. CONCLUSION

In this project, we investigated the significance of feed rate, depth of cut, spindle speed, and coolant on the surface roughness. Using the Taguchi experiment the optimal parameter values are calculated as feed rate 18 ipm, spindle speed 2250 rpm, depth of cut 0.04 in, and coolant on. From the hypothesis testing conducted, we can conclude that the type of cutting tool doesn't affect the surface roughness. Using these parameters, we produced aluminum parts with an average surface roughness of 44.76µin, which is within the specified limits of 45±15µin. The implemented six sigma methodologies helped in improving the C_p value from 0.34 to 2.11 and increased the C_{pk} value from 0.25 to 2.08. This case study indicates that the DMAIC approach is very effective in improving the process so that it can manufacture parts within customer specifications and the customer can even tighten their specifications.

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