Optimization Parameters of tool life Model Using the Taguchi Approach and Response Surface Methodology

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Abstract

The objective of this research is to compare the cutting parameters of turning operation the work pieces of medium carbon steel (AISI 1045) by finding the longest tool life by Taguchi methods and Response Surface Methodology: RSM. This research is to test the collecting data by Taguchi method. The analyses of the impact among the factors are the depth of cut, cutting speed and feed rate. This research found that the most suitable response value; and tool life methods give the same suitable values, i.e. feed rate at 0.10 mm/rev, cutting speed at 150 m/min, and depth of cut at 0.5 mm, which is the value of longest tool life at 670.170 min, while the average error is by RSM at the percentage of 0.07 as relative to the testing value.

Keywords: *Tool life, Taguchi Method, Response Surface Methodology, Cutting parameters*

1. Introduction

The Computer Numerical Control(CNC) machine refers to the automation of machine tools to produce the good quality of work pieces. The production of low cost and good quality of work pieces compose of various factors. The research study found that the parameters are the main factors of lathing to get the job done. Meanwhile it is the factor of fixing tool life. If the selection of parameters is not correct, it will cause the shorter tool life. This will cause the impact of cost of production which could not compete to market effectively. The research found that the Taguchi method and Response Surface Methodology are the suitable parameters.

Response Surface Methodology(RSM) is a statistical and mathematical method that is suitable for development and improving the process, and finding the best value for the process, which in the mean time, test design such as Fractional Factorial Design, Central Composite Design (CCD), Box-Behnken Design(BBD), and orthogonal arrays are designed to use few tests to find relationship of each factor. While Taguchi method is a method that cannot be used to analyze Interaction Effect for every case without any consideration to Confounding of the factor, it does not use sampling principle of test design due to economical test cost requirement. Efficiency of this method depends on the selection of suitable orthogonal array. However, Taguchi method is still popular for engineering work, especially in manufacturing sector.

Noorul and Jeyapaul [1] adopted orthogonal array, Grey relational analysis in the ANOVA using Taguchi method to find suitable level of indentified parameters, and significant association of parameters in order to increase multiple response efficiency of parameters in driller operation for Al/SiC. Later, Mohan et al. [2] adopted Design of Experiments, ANOVA in measuring the data from the collection and analyzed the result with software package MINITAB14 with the objective to increase efficiency of parameters of drilling process of Glass-fiber Polyester material to obtain good surface roughness and low cutting thrust, torque. Then, Kilickap [3] adopted ANOVA, analysis of signal-to-noise ratio to find suitable parameters for the cutting based on Taguchi method. Palanikumar et al. [4] adopted Response Surface Methodology in analyzing the variance for verification model in order to increase efficiency of cutting parameters for surface roughness in the operation of PCD cutting machine with Al/SiC material. Tosum and Ozler [5] used the Taguchi method to investigate multiple performance characteristics and the improvement of optimal cutting parameters in hot turning operations. Thanizhmanil et al. [6] proposed the efficient use Taguchi's parameter design to obtain optimum condition because it leads to minimum number by experimental and lower cost. Rossella *et al.* [7] proposed a new optimization method of the manufacturing parameters using Taguchi method. They found that the experiment design of the orthogonal array of the Taguchi method can identify the significant foaming parameters the adjusted the process.

The above researches showed that Taguchi method and Response Surface Methodology are techniques that increase efficiency successfully applied in industrial work for the best option of the process parameters in the area of machinery. Taguchi method has potential for saving test time and cost relating to the product or manufacturing process development, and quality improvement.

Therefore the study of behavior and relationship of parameters are the main factors namely depth of cut, cutting speed and feed rate. These parameters can determine the CNC program to modify easily. The researcher has chose such parameters to collect and analyze the information as the form of Taguchi method. The appropriate value of tool life is calculated by Response Surface Methodology.

2. Experimental procedure

2.1 Test Specimen

This research conducted a cutting test with an automatic machine called PINACHO, RAYO 180 model, using an Insert of KENNAMETAL-KC5010 with Nose Radius of 0.4 millimeter, and SHELLDROMUS OIL B for heat ventilation. The material used in the cutting is medium carbon steel(AISI 1045).

2.2 Tool life measurement

The cutting for calculating the working life of tool life is shown as the table of orthogonal array L_9 by cutting the part at 10 rounds of one piece to get the cutting length at 1,000 millimeter and stopping watch and checking the wearing out by the Toolmaker's Microscope of TM 505 which the lenses of 30 times and measure every 1,000 millimeter until the size of the Flank Were are more than 0.6 millimeter(VB max>0.6 millimeter)

Fig 1: Show machine used to measured of tool life and Flank Were (VB)

2.3 Taguchi Method and design of experiment

The Taguchi method is a quality tool that helps improve the work efficiently. It is possible to select suitable factors as shown in Table 1, which indicates factors and their levels in the cutting experiment with CNC machine, which contains 3 factors, and each factor has 3 levels. The table 2 is shown the form of orthogonal array L_9 for data collection. The researcher collects data by 9 conditions. Each condition will be determined by the factors for instance the the first condition is identified by the depth of cut at 0.5 mm., cutting speed at 150 m/min and feed rate at 0.10 mm/rev as well. Therefore, the orthogonal array is selected with $L_9(3^3)$ method which gave the order of experiment as shown in Table 3.

As mentioned earlier, Taguchi method is used for tuning the turning process by optimizing the process parameters for best tool life. In general, the parameter optimization process of the Taguchi method is based on 8-steps of planning, conducting and evaluating results of matrix experiments to determine the best levels of control parameters [8]. Those eight steps are given as follows.

- Identify the performance characteristics (responses) to optimize and process parameters to control (test).
- Determine the number of levels for each of the tested parameters.
- Select an appropriate orthogonal array, and assign each tested parameters into the array.
- Conduct an experiment randomly based on the arrangement of the orthogonal array.
- Calculate the *S/N* ratio for each combination of the tested parameters.
- Analysis the experimental result using the *S/N* ratio and ANOVA test.
- Find the optimal level for each of the process parameters.
- Conduct the confirmation experiment to verify the optimal process parameters.

Table 1: Cutting parameters and their levels

Factors	Cutting Parameters	Levels			unit
		1	2	3	
1	Depth of cut (D)	0.50	1.00	1.50	mm
2	Cutting speed (Vc)	150	200	250	m/min
3	Feed rate (F)	0.10	0.15	0.20	mm/rev

Table 2: Table of Taguchi designs (Orthogonal Arrays L_9)

Experiment Number	Cutting parameter level		
	A	B	C
	Depth of cut	Cutting speed	Feed rate
1	1 (Level 1)	1 (Level 1)	1 (Level 1)
2	1 (Level 1)	2 (Level 2)	2 (Level 2)
3	1 (Level 1)	3 (Level 3)	3 (Level 3)
4	2 (Level 2)	1 (Level 1)	2 (Level 2)
5	2 (Level 2)	2 (Level 2)	3 (Level 3)
6	2 (Level 2)	3 (Level 3)	1 (Level 1)
7	3 (Level 3)	1 (Level 1)	3 (Level 3)
8	3 (Level 3)	2 (Level 2)	1 (Level 1)
9	3 (Level 3)	3 (Level 3)	2 (Level 2)

Table 3: Experimental layout based on an L_9 orthogonal array

Experiment number	Cutting Parameter Level			Parameter setting
	A	B	C	
	Depth of cut	Cutting speed	Feed rate	
1	0.5 (Level 1)	150 (Level 1)	0.10 (Level 1)	A1B1C1
2	0.5 (Level 1)	200 (Level 2)	0.15 (Level 2)	A1B2C2
3	0.5 (Level 1)	250 (Level 3)	0.20 (Level 3)	A1B3C3
4	1.0 (Level 2)	150 (Level 1)	0.15 (Level 2)	A2B1C2
5	1.0 (Level 2)	200 (Level 2)	0.20 (Level 3)	A2B2C3
6	1.0 (Level 2)	250 (Level 3)	0.10 (Level 1)	A2B3C1
7	1.5 (Level 3)	150 (Level 1)	0.20 (Level 3)	A3B1C3
8	1.5 (Level 3)	200 (Level 2)	0.10 (Level 1)	A3B2C1
9	1.5 (Level 3)	250 (Level 3)	0.15 (Level 2)	A3B3C2

Table 4: $L_9(3^3)$ Orthogonal Array, Experiment results and S/N ratio

Experiment Number	Cutting Parameters			Measure Tool Life (Min)	S/N ratio
	Depth of cut	Cutting speed	Feed rate		
1	0.5	150	0.10	670.17	56.5237
2	0.5	200	0.15	308.10	49.7738
3	0.5	250	0.20	114.75	41.1951
4	1.0	150	0.15	253.46	48.0782
5	1.0	200	0.20	182.00	45.2014
6	1.0	250	0.10	176.85	44.9521
7	1.5	150	0.20	124.65	41.9138
8	1.5	200	0.10	239.85	47.5988
9	1.5	250	0.15	90.77	39.1588

As the reason of decreasing the numbers of testing suit to the condition by the consideration of the ratio of impact (S/N ration). The analysis of impact between the factors of Higher is better. Type problem for tool life(eq.1) and the analysis of variance(ANOVA) to test the difference of factor levels.

Higher is Better Type Problem for Tool Life

$$S/N = -10\log\sum_{i=1}^{n}\frac{1/y_t^{\ 2}}{n} \qquad (1)$$

2.4 Response Surface Methodology: RSM

Response surface methodology:(RSM) is usually considered in the context of experimental design as a statistical method for modeling and analyzing of problems in which different variables affect a response of interest. The first step in RSM is to determine a suitable approximation for the actual functional relationship between the response variable y and a set of independent variables as follows; [9].

$$y = \beta_0 + \sum_{i=1}^{k}\beta_i x_i + \sum_{i=1}^{k}\beta_{ii}x_i^2 + \sum\sum_{i<j}\beta_{ij}x_i x_j + \varepsilon \qquad (2)$$

Where β are the coefficients which are calculated using an appropriate method such as the least square method. When resulted estimated surface is an adequate approximation of the true response function, the results will be approximately equivalent to analysis of the actual system. The model parameters can be approximated whenever proper experimental designs are used to collect the data.

3. Determination of cutting parameters

Test result collection according to the order of the experiment in Table 4, and analyze S/N ratio of tool life is as follows;

This section provides the results of S/N ratio, main effect plot and ANOVA. From the results of mean S/N ratio and ANOVA analysis, the optimal combination of cutting parameters is achieved and verification tests have been performed to predict the improvement.

3.1 Analysis of the signal-to-noise(S/N) ratio

In Taguchi method, the term signal represents the desirable value, and noise represents the undesirable value. Process parameters with the highest S/N ratio always give the best quality with minimum variance [10]. The S/N ratio for each parameter level is calculated by finding the average of S/N ratios at the corresponding level. Fig 2 shows the response table for S/N ratio of tool life for larger is better obtained for different parameter levels.

Response Table for Signal to Noise Ratios of **Tool Life Larger is better**

Level	D	Vc	F
1	49.16	48.84	49.69
2	46.08	47.52	45.67
3	42.89	41.77	42.77
Delta	6.27	7.07	6.92
Rank	3	1	2

Fig.2 Response table for Signal to Noise Ratios of tool life

The analysis of S/N ratio of tool life found that the first factor that causes tool life to be great is cutting speed, having feed rate and depth of cut as secondary factors, respectively. After that, the analysis is made to determine suitable factor of each main factor from S/N ratio as shown in Fig.3.

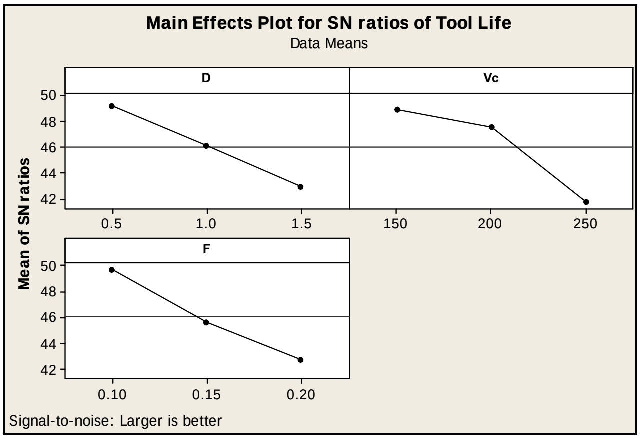

Fig.3 Main effects plot for Signal to Noise Ratios of tool life

In the impact analysis of S/N ratio, factor level will be selected to give maximum S/N ratio as the most suitable factor level. The selection of the most suitable factor level from the graph found that level of factor that causes tool life to be great is when level of depth of cut is 0.5 mm, level of cutting speed is 150 m/min and level of feed rate is 0.10 mm/rev.

3.2 Analysis of variance

The ANOVA study performed to investigate the statistical significance of the process parameters affecting the response(tool life). This is achieved by separating the total variability of the S/N ratios, which is measured by the sum of the squared deviations from the total mean of the S/N ratio, into contributions by each of the process parameters and the error [11]. F-test is carried out to judge the significant parameter affecting the tool life. The larger F-value affects more on the performance characteristics.

Analysis of Variance for SN ratios of **Tool Life**

Source	DF	Seq SS	Adj SS	Adj MS	F	P	
D	2	59.044	59.044	29.522	15.55	0.060	
Vc	**2**	**84.842**	**84.842**	**42.421**	**22.35**	**0.043**	**Significant**
F	2	72.488	72.488	36.244	19.10	0.050	
Residual Error	2	3.796	3.796	1.898			
Total	8	220.169					

Fig.4 Results of ANOVA using data from Signal to Noise Ratios for tool life

Fig.4 shows the results of ANOVA for tool life for a level of significance of 5%(0.05). From ANOVA Fig.4, it is found that, Vc(Cutting Speed) is the significant parameter on tool life. The depth of cut and feed rate is found to be insignificant from ANOVA for tool life study.

4. Development of Response Surface Model

The analysis with Taguchi method mentioned above is an analysis only for the main factors that affect tool life without any consideration of correlation between factors. Therefore, the researcher has performed Response Surface Regression in the analysis of correlation between factors. Analysis with response optimizer function that finds the best value for the third factor at the significant level of 95% by response analysis as follows;

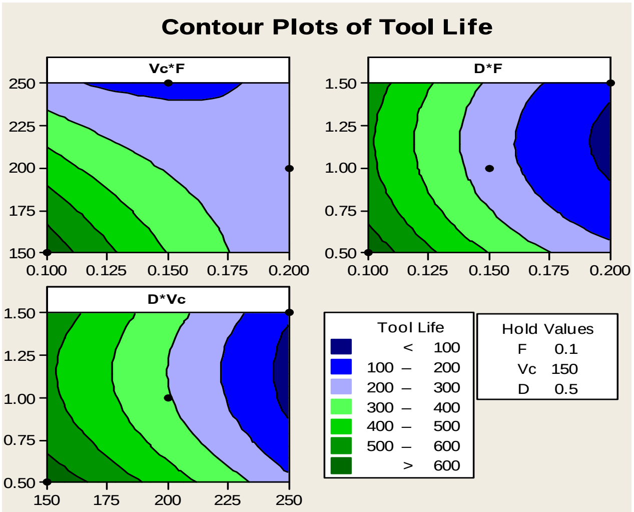

Fig.5 Contour Plots of tool life

The above analysis found that contour plots of tool life is a curve. Therefore, mathematical model suitable for predicting suitable value is Quadratics model by considering the Full Quadratics model as shown in equation 3, which the coefficients of factors that affect response value are as shown in Table 5.

Table 5: Coefficients of Factors that affect Response Value

Term	Coef of tool life
Constant	2800.51000
D	-1536.13000
Vc	-5.83803
F	-11866.63333
D*D	215.78000
Vc*Vc	-0.00205
F*F	35796.66667
D*Vc	4.44453
D*F	20.53333

With the above coefficients of factors that affect response value above, a mathematical model equation can be built as follows;
Mathematical model for forecasting tool life

$$\text{Tool Life} = 2800.51 - 1536.13D - 5.83803Vc - 11866.63333F + 215.78D^2 - 0.00205Vc^2 - 35796.66667F^2 + 4.44453DVc + 20.53333DF \quad (3)$$

The model of the appropriate parameters of tool life as the 3rd equation is the comparison between the real value and the forecasting value of the model by the parameter as shown in Table 4 as follows:

Table 6: Comparison of actual value and forecasting value of tool life

Experiment Number	Cutting parameters			Tool life		
	Depth of cut	Cutting speed	Feed rate	Actual	Forecasting	%Error
1	0.5	150	0.10	670.17	670.230	0.01%
2	0.5	200	0.15	308.10	308.207	0.03%
3	0.5	250	0.20	114.75	114.917	0.15%
4	1.0	150	0.15	253.46	253.520	0.02%
5	1.0	200	0.20	182.00	182.107	0.06%
6	1.0	250	0.10	176.85	177.017	0.09%
7	1.5	150	0.20	124.65	124.710	0.05%
8	1.5	200	0.10	239.85	239.957	0.04%
9	1.5	250	0.15	90.77	90.937	0.18%
Average						0.07%

The information in Table 6 shows the result from the comparison between actual value and forecasting value which found that the forecasting values of tool life has the average error of only 0.07%.
The T-Test for the analysis of data difference from the assumption that the average the actual value is not equal to the average forecasting value at the significant level of 0.01 found that P-Value is 0.0001. Therefore, it is concluded that the main assumption should be rejected and the secondary assumption should be accepted, which the average actual value is equal to the average forecasting value.
For finding suitable point of the factors, which is the best point for this experiment using Minitab Release 15, Response Optimizer function, the researcher selected Desirability Function to find suitable value of the factors. After the assessment, the obtained values are as follows;

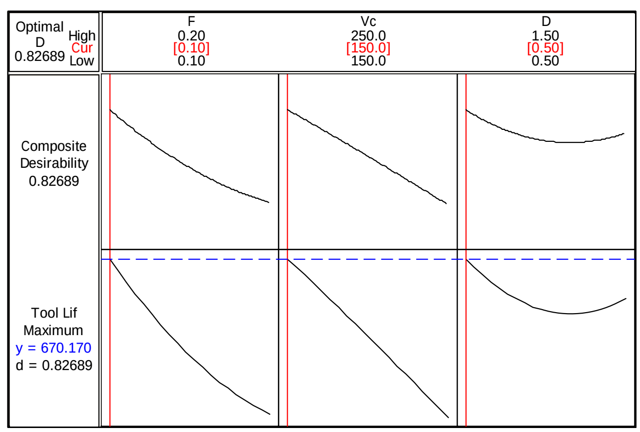

Fig.6 the appropriate value of each factor which effect to tool life

The appropriate value of tool life is the maximum and longest value at 670.170 min. The determination of depth of cut as 0.5 mm, cutting speed as 150 m/min, and feed rate as 0.10 mm.rev as the satisfaction as the suitable value at 0.82689 as well.

5. Conclusion

As the parameter testing of lathing work pieces as depth of cut, cutting speed and feed rate as the surface response of tool life by Taguchi method and Response Surface Methodology as both appropriate value of both methods as shown in Table 7

Table 7: The comparison of cutting parameters by Taguchi method and RSM

Symbol	Cutting Parameters	Tool Life(min)		
		Taguchi	RSM	Unit
D	Depth of cut	0.5	0.5	mm.
Vc	Cutting speed	150	150	m/min
F	Feed rate	0.10	0.10	mm/rev
		670.170	670.230	

As can be seen from Table 7 it found that the suitable of response of tool life by both methods will get the suitable values namely depth of cut at 0.5 mm. cutting speed at 150 m/min and feed rate at 0.10 mm/rev. All mentioned values cause the longest tool life at 670.170 min by Taguchi method and 670.230 by RSM respectively.

6. References

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