Response Surface Methodology (RSM) Model to Evaluate Surface Roughness in Machining of Titanium Alloy (Ti6–Al–4V) Using End Milling Process

Asmizam Mokhtar and Nurul Hidayah Razak

Abstract The inspiring working demand in surface finish product of manufacturing process will step up the world into the next level. This situation will drive its effect on product appearance, function and reliability. The objective of this study is to improve a better understanding of the effects of cutting parameters such as speed, feed and axial depth of cut on the surface roughness and to build up a response surface methodology (RSM) model. An attempt has been made to achieve finest cutting conditions with respect to center line average roughness (R_a) measured in the current study with the help of response optimization technique. The design of experiment (DOE) has been used to carry out the modelling and analysis of the influence of process variables on that method. Analysis of variance (ANOVA) has been done to verify the fit and competence of the established a mathematical model. Based on the model, feed rate is the most significant value that influence the surface roughness value in milling Titanium alloy (Ti6–Al–4V).

Keywords Surface finish · Surface roughness · Response surface methodology (RSM) · Titanium alloy (Ti6–Al–4V)

1 Introduction

The challenge of modern machining industries dedicated on the achievement of high quality, in term of workpiece dimensional accuracy, surface finish, high production rate, less wear on the cutting tools, an economy of machining in terms of cost saving and an increase of the performance of the product with reduced environmental impact.

The ability to control the process for better quality of the final product is very importance. The surface texture is apprehensive with the geometric irregularities of the surface of a solid material which is well-defined in terms of surface roughness, waviness, lay and flaws. Surface roughness (R_a) consists of the surface texture,

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including feed marks produced by the machining process. The quality of a surface is a pointedly important factor in assessing the efficiency of machine tool and machined parts. Therefore, a decent quality machined surface essentially improves fatigue strength, corrosion resistance and creep life [1].

Titanium alloys also ease of use makes it the best application for use in a few industries, similar to the aviation, restorative, marine, and chemical processing industries. These reasons may be utilized in the formation of such specialized things as Aircraft turbines Engine, components Aircraft, basic components Aerospace fasteners, high-execution programmed parts Marine applications and sports equipment [2]. The end milling processing is a standout amongst the most imperative procedures which is generally used to create the primary parts in numerous ventures, for example, the form and pass on parts, the aviation parts, and the car parts [3].

End Milling is a process of generating machined surfaces by progressively removing a predetermined amount of material from the workpiece. Axis of the tool rotation is perpendicular to feed direction. End Milling is an interrupted cutting operation. In these operations, the tool is constantly being heated and reheated [4]. The surface roughness is assuming an essential job to assess the nature of a workpiece. Surface texture parameters and statistical functions are superior in characterizing and evaluating surface quality and corresponding functionality-related performance of machined components, when compared with the traditional means in which only single valued standard surface parameters being adopted [5].

Reasonable selection surface texture characterization and statistical functions could give more specific and complete descriptions of the micro geometry and functionality related properties for the machined surfaces having identical values for primary indexes. Then, effective correlation of the selective surface texture characterization parameters and statistical functions with specific functionality-related properties are implemented. These symbols provide a standard system of determining and indicating surface finish. The inch unit for surface finish measurement is micro inch (µm), while the metric unit is micrometre (µm) [6].

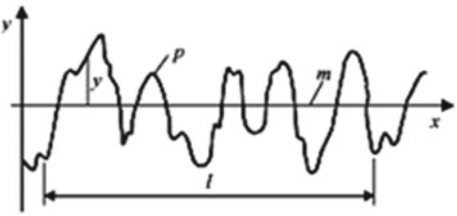
Roughness is defined as closely spaced, irregular deviation on a scale smaller than that waviness. It is caused by the cutting tool or the abrasive grain action and the machine feed. The roughness of surface may be superimposed by waviness. There are most two types significant of surface roughness as follow:

i. Roughness Average, R_a—Roughness height is the deviation to the center line in micro inches or micrometres.
ii. Roughness Depth, R_z—Roughness width is the distance between successive roughness peaks parallel to the nominal surface in inches or millimetres.

Figure 1 indicates standard phrasing and symbol to determine value of surface roughness. The symbol *p* is the shape of any predetermined area through a machined surface on a plane that is opposite to the surface.

Roughness width cut off l (i.e., testing length) is incorporated into the estimation of normal surface roughness. The mean line *m* of the profile *p* is found with the goal that the entirety of the regions over the line (inside the testing length l) is equivalent to the whole of the regions underneath the line [7].

Fig. 1 Surface roughness definition



Despite the different surface finish parameters, the roughness average Ra is the most used international parameter of surface roughness. It is defined as Eq. (1):

$$R_a = \frac{1}{l}\int_0^1 |y(x)|dx \tag{1}$$

2 Experimental Setup

2.1 Design of Experiments

Response Surface Methodology (RSM) is a collection of statistical and mathematical methods that are useful for the modelling and optimization of the engineering problems. In this technique, the main objective is to optimize the responses that are influencing by various parameters. This method also quantifies the relationship between the controllable parameters and the obtained response [8, 9].

This study uses the Box-Behnken design in the optimization of experiments using RSM to understand the effect of important parameters [10–13]. Three levels of cutting parameters are selected to investigate the machinability of this alloy which is consist of range feed rate, 0.05, 0.1, 0.15 mm/rev, different value of cutting speed, 50, 100 and 150 m/min and different value of depths of cut such as 0.2, 0.5 and 0.8 mm were selected [14].

The values of parameters in conducting the experiment are shown in Table 1 and design of experimental shown in Table 2.

Table 1 Machine parameter and level

Destination	Process parameters	Level		
		−1	0	1
X1	Cutting speed (m/min)	50	100	150
X2	Feed (mm/rev)	0.05	0.1	0.15
X3	Axial depth (mm)	0.2	0.5	0.8

Table 2 Design values of parameters generated by Minitab 18

Run order	Cutting speed, Vs (m/min)	Feed, f (mm/rev)	Axial depth, ap (mm)
1	100	0.1	0.5
2	150	0.1	0.8
3	50	0.1	0.2
4	50	0.15	0.5
5	50	0.1	0.8
6	150	0.15	0.5
7	150	0.1	0.2
8	100	0.15	0.2
9	50	0.05	0.5
10	100	0.1	0.5
11	100	0.15	0.8
12	100	0.1	0.5
13	150	0.05	0.5
14	100	0.05	0.8
15	100	0.05	0.2

2.2 *Workpiece and Cutting Tool Material*

Titanium alloy also has numerous applications in the medical industry and biocompatibility of titanium alloy is excellent, especially when direct contact with tissue or bone is required. The mechanical properties of titanium alloy shown in Table 3 and chemical composition are shown in Table 4.

The toolholder with an indexable insert in Figs. 2 and 3, examples as coated carbide is very good for cutting a hard material. Its positive cutting edge removes metal by slicing through the material, rather than by scraping.

The configuration ought to be adequate to fit a quadratic model, that is, one containing squared terms, results of two variables, straight terms, and a catch. The

Table 3 Mechanical properties of titanium alloy (Ti6–Al–4V)

#	Mechanical properties	Value
1	Hardness, Vickers	349 HV
2	Tensile strength, ultimate	950 MPa
3	Tensile strength, yield	880 MPa
4	Modulus of elasticity	113.8 GPa
5	Poisson's ratio	0.342
6	Shear modulus	44 GPa
7	Shear strength	550 MPa

Source ASM Material Data Sheet

Table 4 Chemical Composition (% by weight) of Titanium Alloy (Ti6–Al–4V)

Element	Min (% by weight)	Max (% by weight)
Al	5.5	6.5
C	–	0.08
Fe	–	0.25
H	–	0.015
N	–	0.05
Ti	Balance	
O	–	0.2
V	3.5	4.5

Source Fine tubes product Material

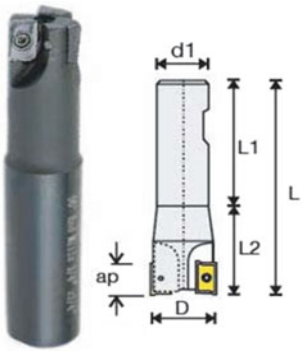


Fig. 2 End mill with indexable toolholder. *Source* www.ceratizit.com

Fig. 3 Shape of coated carbide insert. *Source* www.ceratizit.com

proportion of the quantity of trial focuses on the number of coefficients in the quadratic model ought to be sensible [6].

This experiment was conduction in wet machining condition on a CNC Milling Machine HAAS VF6 by slotting cutting process equipped with a spindle max of 3000 rpm. The type of cutting tools used is coated carbide by toolholder diameter 16 mm. One pass machining cycle at Y Axis was used to determine the machining surface condition [15].

Two common methods of surface roughness measurement in engineering practice are described, including the instrumentation involved and brief description of surface roughness requirements in engineering practice. All the surface roughness measurement data collected. The result of the surface roughness must be less than 1 μm for better surface finish, if more than that value; the process of machining by using end milling will be repeated [16].

Then the value of surface roughness was measured by surface perthometer manufactured by Mahr model (Surf PS1). Roughness average definitions are shown in Fig. 4.

The observation of cutting surface were taken for each cutting process each sample and were averaged in order to get the significant value of Roughness average (R_a) [17]. The type of insert and machining material set up on machine and cutting tool are shown in Fig. 5.

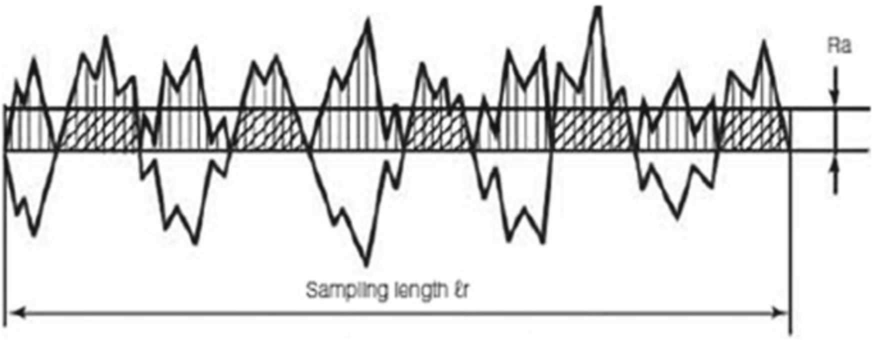


Fig. 4 Arithmetical mean height (R_a). *Source* www.keyence.com

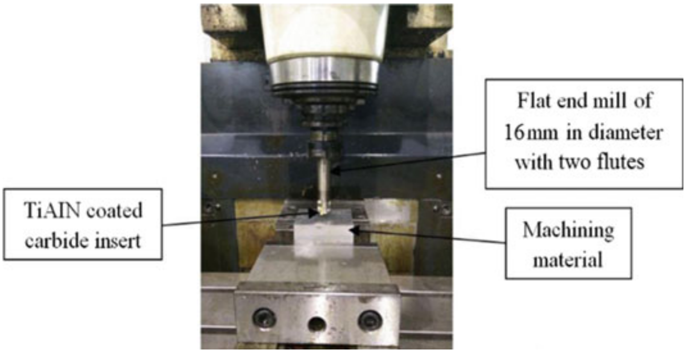


Fig. 5 Experiment setup of cutting tool and material

2.3 Response Surface Methodology

The fundamental target is to optimize the response between surface that is affected by different process parameters. RSM is measured the connection between the information parameters and the acquired reaction surfaces [18]. The second-order polynomial scientific model for surface roughness is created as Eq. (2):

$$Y = C_0 + \sum_{j=1}^{k} C_j x_j + \sum_{j=1}^{k} C_{jj} X_j^2 + \sum_{i<} \sum_{j=2}^{k} C_{ij} X_i X_j \tag{2}$$

where Y is the corresponding response (surface roughness, SR) yield by the various variables and *X1* (1, 2, 3 … n) are coded levels of n quantitative process variables, the term 0 *C, jC, jjC* and *ijC* are the second order regression coefficients. Equation (2) can be written as Eq. (3):

$$\begin{aligned} Y = C_0 &+ C_1X_1 - C_2X_2 - C_3X_3 \\ &- C_{11}X_1^2 + C_{12}X_2^2 + C_{13}X_3^2 \\ &- C_{13}X_1X_2 - C_{23}X_1X_3 + C_{33}X_2X_3 \end{aligned} \tag{3}$$

where 1, 2, 3 *X X*, *X* are feed rate (mm/tooth), axial depth (mm) and cutting speed (m/min) respectively [19–23]. The equations of the fitted model for SR are represented in Eq. (4):

$$\begin{aligned} Y = 0.0078 &+ 0.02109X_1 - 8.69X_2 \\ &- 0.999X_3 - 0.000063X_1^2 \\ &+ 70.2X_2^2 + 0.057X_3^2 - 0.0834X_1X_2 \\ &- 0.00038X_1X_3 + 9.53X_2X_3 \end{aligned} \tag{4}$$

Besides, to make sure the overall values are fit and lack of errors, *P*-values were identified. Table 5 shows the corresponding *P*-values for the data machining surfaces. Based on Table 5, the *P*-values show that the mathematical model is significant and adequate in order to determine the value of surface roughness. The coefficients generated can be used for mathematical modeling.

3 Result and Discussion

The analysis of variance is exhibited in Table 5. The sufficiency of the model is confirmed utilizing using ANOVA. At a confident level of 95%, the model is checked for its sufficiency. In Table 5, model is satisfactory because of the way that the *P*

Table 5 Analysis of variance for roughness average (R_a)

Source of variation	Degree of freedom	Sum of square	Mean of square	F-value	P-value
Regression	9	0.540678	0.060075	4.96	0.046
Linear	3	0.063477	0.021159	1.75	0.273
Square	3	0.221527	0.073842	6.10	0.040
2-way interaction	3	0.255674	0.085225	7.04	0.030
Residual error	5	0.060550	0.012110		
Lack-of-fit	3	0.046064	0.015335	2.12	0.336
Pure error	2	0.014486	0.007243		
Total	14	0.601228			

value of lack-of-fit is not significant. This suggests that the model could fit, and it is sufficient. Hence, the model is satisfactory and there is some indicator to measure the viability of the model that worked in the estimation of surface roughness prediction data [24–27]. The Fig. 6 shows that normal probability during response is average at the value of value of 95%.

The variation of the effect of cutting parameter against cutting speed, feed and axial depth are represented in Fig. 7. From the graph, the value of surface roughness is increasing as the feed increases.

This condition happens due to the increase in heat between the tool and the workpiece, thus causing the tool to be exposed to damage because of the high frictional

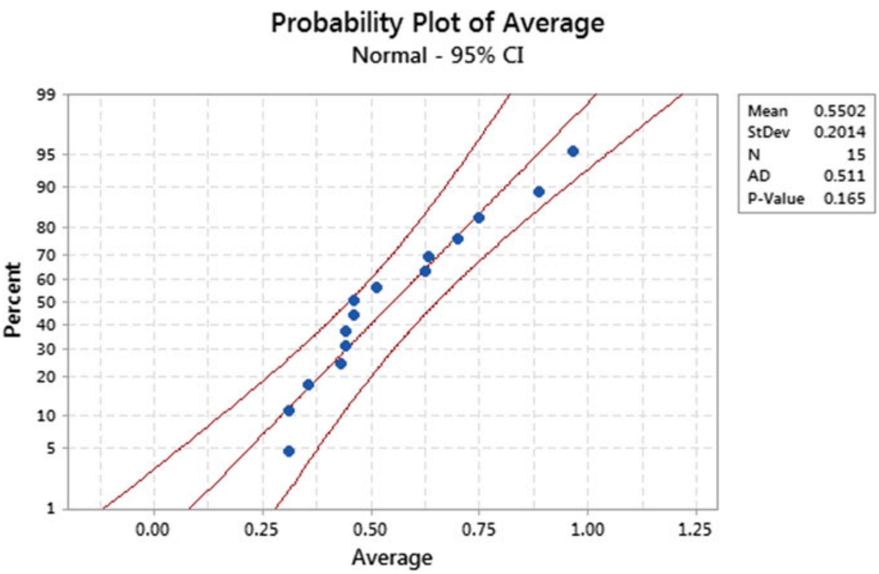


Fig. 6 Normal probability plot

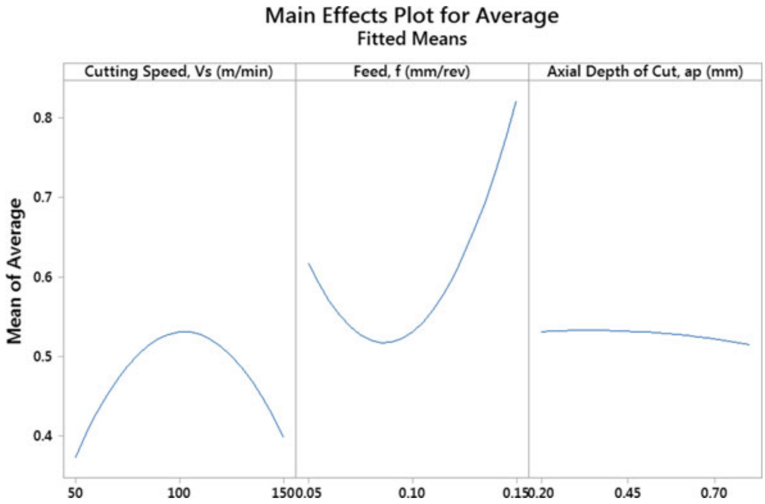


Fig. 7 Main effect of machine parameter

force between the tool and workpiece. Effect on cutting speed and axial depth shows the same pattern. When the value of cutting speed is low it will give the best condition of surface on machine material. Means that, feed rate minimum will give a better surface finish.

The effect of feed rate depends on other factors, mainly spindle speed. This is because feed rate and spindle speed involve movement which then decides the thermal barrier and frictional forces between tool and workpieces. According to the Fig. 8, surface roughness value becomes more significant as the cutting speed decreasing. From the graph also, it shows that value of feed, f gives more significant result to the specimens.

Variation of surface roughness demonstrates the effect of surface roughness against the feed rate and cutting speed. It very well may be seen that the feed has the most predominant impact of surface roughness, trailed by the axial depth of cut and cutting speed. Littler cutting powers cause less vibration and give a superior surface completion Fig. 9a. It is obvious from Fig. 9b that surface at roughness increments with the reduction in feed rate.

A low feed rate uniforms the external surface accordingly expanding the surface completion. Another factor to consider is cutting velocity. It is comprehended that an expansion in cutting pace improves surface quality. This outcome supports the disagreement that sufficiently high cutting rates reduce cutting powers together giving a superior surface achievement. Subsequently, better surface roughness can be acquired by utilizing high cutting speed, low axial depth of cut, and low feed rate.

In Fig. 10 demonstrates the predicted outcomes closely concur with the experimental qualities. Thusly, the model of the response surface strategy can be acknowledged too. From this graph, the process of relationship between prediction and experimental can be observed and determined during this experiment. This result gives

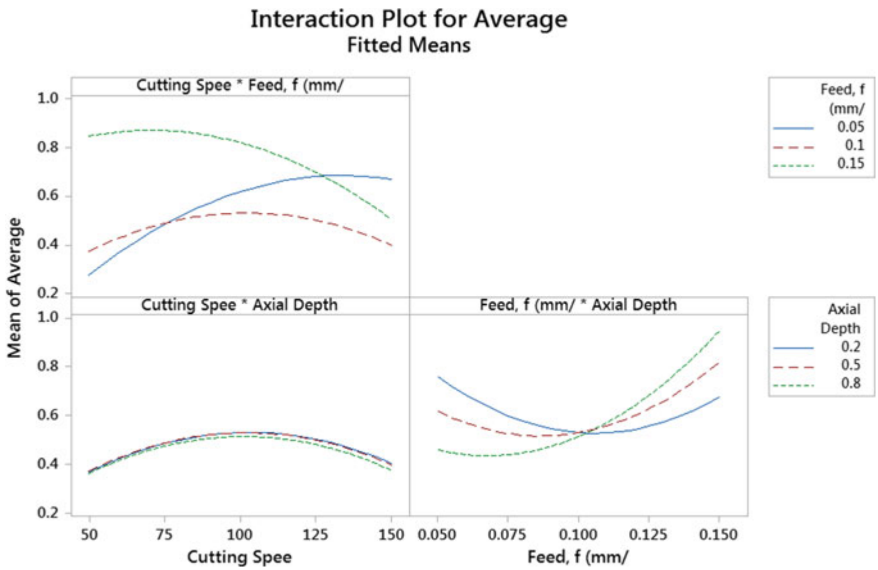


Fig. 8 Interaction plot of machine parameter

better understanding of cutting process during experiment and also result that we get from prediction method for validation process.

4 Conclusions

In this investigation, RSM has been utilized to decide the expectation of surface roughness by machining titanium alloy (Ti6Al4V) with coated carbide for different input parameters to be specific the feed rate, axial depth of cut, and cutting speed. The feed rate has the most significant impact surface roughness, followed by feed rate, axial depth of cut and cutting speed. The higher value of feed rate highly impacts the value of surface roughness. The RSM model can effectively use to optimize the machining parameters to improve the surface roughness of workpiece machined.

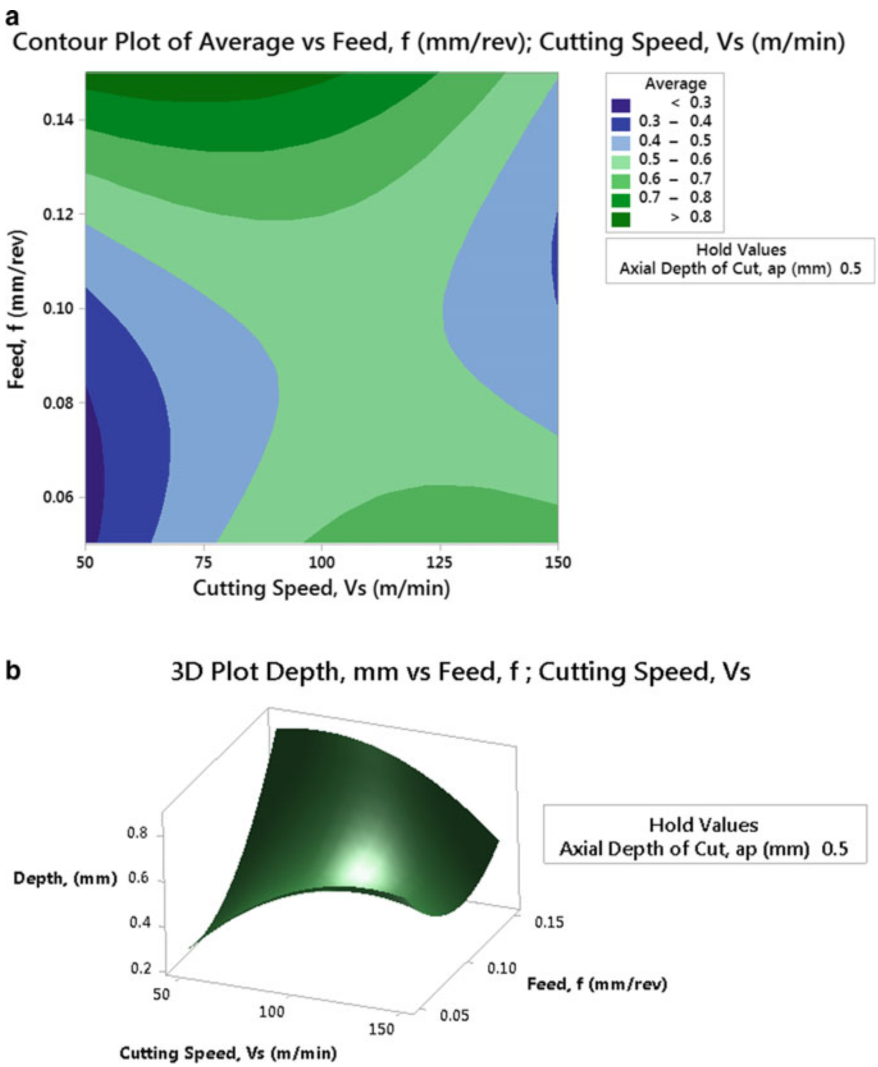


Fig. 9 **a** 2D contour plot of surface roughness, **b** 3D contour plot of surface roughness

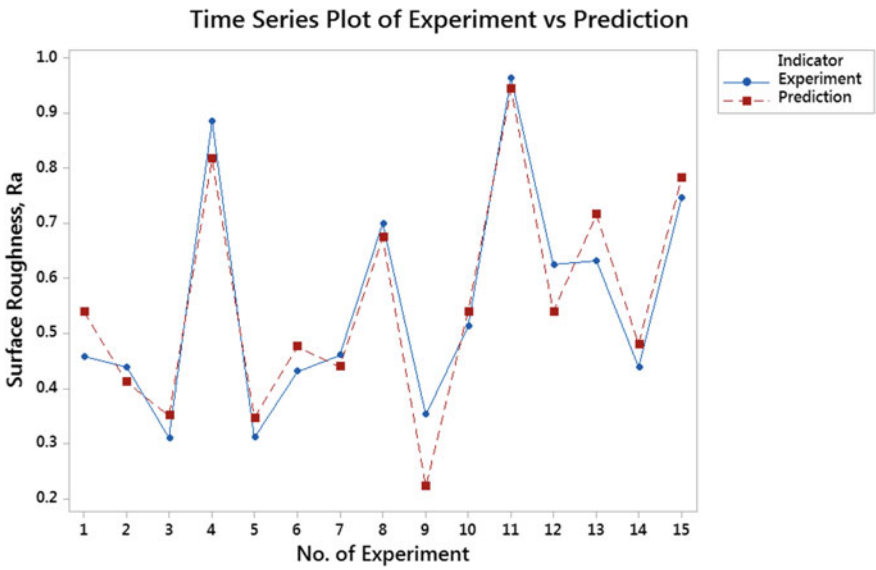


Fig. 10 Value of surface roughness between predicted and experimental

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