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Uncertainty and Sensitivity Analysis of Surface Quality in Machining of AISI 4140 Alloy Steels

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Abstract: Uncertainty is the likelihood that a quantity will statistically deviate from the desired value. Though quality of a machined surface are attributed by many parameters, in this investigation, three surface textures namely $R_a, R_z\ and\ R_t$ are considered to measure the uncertainties in quality of a surface during machining of AISI 4140 Alloy Steel. First, these three surface textures are modeled using RSM with speed, feed, and depth of cut as input parameters and thereafter uncertainties and sensitivities are measured. It is observed that the uncertaintie of the model $R_a, R_z\ and\ R_t$ is 0.0440, 0.2567, and 0.2568 respectively using the Monte Carlo Simulation. Principal contributors in uncertainty and sensitivity for $R_a, R_z, and\ R_t$ are feed, depth of cut, and depth of cut respectively.

Keywords: Surface textures; Modelling; Uncertainty, Sensitivity; Monte Carlo Simulation.

1. Introduction

Uncertainty is the range of possible values within which the true value of the measurement lies. Combination of input parameters or repeated measurements may cause uncertainties. Manufacturing an item precisely to the desired size is not achievable in engineering. The precision of a measurement depends on a variety of elements, including the environment, the operator's skill, and the measurement process. Therefore, any quantity of a manufactured good that is measured is subject to uncertainty, and the measurement results are incomplete without specific mention of uncertainty. The probabilistic character of this uncertainty indicates that we know only a portion of the value of the quantity. Therefore, all measured quantity of a manufactured product are subjected to uncertainty and the measured result is incomplete in a sense. This uncertainty have a probabilistic nature and depicts incomplete knowledge of the quantity value. Uncertainty propagates based on the variables. The uncertainty is expressed either by absolute error Δx or by relative error, $\Delta x/x$. In most of the situation in manufacturing the uncertainty is quantified by the standard deviation, σ. If we can presume the distribution of this error, we can easily fix the confidence limits which describes the region within which the true value of the variable may be found. For example, if the error of a particular measurement is normally distributed, it can be stated approximately standard deviation from the central value x will cover approximately 68% cases.

Turning is one of the simple and old machining operations where excess materials are removed to convert the blank into the desired shape. In any machining process, an error is the deviation of the actual value from the desired value. Uncertainties are the probabilistic value of this error. Users as well as manufacturers must have sufficient knowledge about these uncertainties to avoid scrap. Major part of the previous work dealt with only R_a to denote the surface characteristics but there can be a different surface with the same R_a is the average value only. The machining parameters as for example like speed, feed and depth of cut, etc. have the most dominant effect on the machining performance. Therefore, it becomes more important to select them carefully to obtain a machined component with high quality & accuracy. Uncertainty is an inherent property in any manufacturing process. If these parameters are not selected properly, the uncertainty of the process may increase. The uncertainty may be classified into two types, one is systematic and another is random. Systematic uncertainty can be eliminated, but random uncertainty cannot be eliminated as they arise from the actual measurement of the product. Therefore, random uncertainty can only be reduced. To evaluate the uncertainty, it is important to consider those factors which have most influences on the responses. Fig.1 shows the factors that affect the uncertainty. In this study, cutting speed, feed, and depth of cut, are considered as factors that affect the uncertainty of the responses.

It is also the estimated range that considers all the possible outcomes of the measurement within a confidence level.

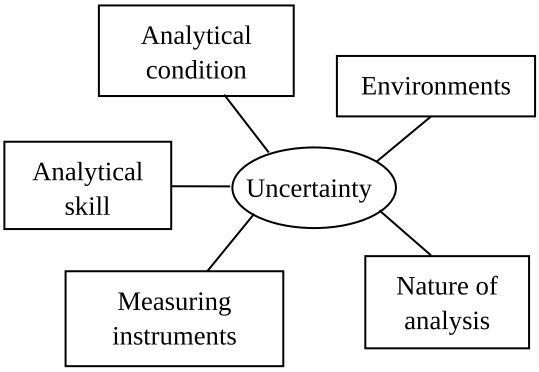


Fig. 1: Influencing Variables in Uncertainty

2. Related Work

J Wen et al. [2] observed that CNC turning is especially suitable for hard materials and opined that selection of machining parameters is very important due to its narrow range of acceptable values. Li Hao et al. [3] performed a multi-response optimization where they maximized quality and flexibility and minimized the cost. Pandey et al [4] applied fuzzy approach to optimize the drilling process keeping minimum bone tissue damage. Singh et al. [5] used Taguchi's design of experiment and fuzzy approach, considering 4 parameters with 5 levels to optimize bead geometry in submerged arc welding. Li et al. [6] used a special type of GA to perform an optimization of performance of Ti alloy. Suresh et al. [7] applied grey-fuzzy to avoid uncertainties in the experimentation. M. Libah et al. [8] compared wiper and ceramic tools based on roughness parameters (R_a, R_t, $and\ R_z$) during hard turning of AISI4140 steel. They found out the most influencing parameters and optimal cutting conditions. They used RSM and ANOVA for modelling. But surface roughness (SR) parameters have not been considered in lateral direction. Akkus et al. [9] compared artificial neural network, and fuzzy technique for modelling of SR based on mean squared error [MSE] during hard turning of AISI 4140 steel They used MATLAB for ANN and fuzzy logic and Minitab for variance analysis. Aggarwal et al. [10] considered different types of regression models namely multiple regression models, Random forest, and Quantile regression for surface roughness parameters during hard turning of AISI 4340 steel. They opined that feed rate is the most influencing factors and multiple regression models are most suitable when surface roughness is below 1 micrometer. Geier et al. [11] developed empirical models of SR parameters R_a, R_t, and R_z during finish turning of AISI 4140 steel with wiper cutting tools. They developed linear models of surface parameters. Gadelmawla et al. illustrated various surface parameters, and developed a new vision-based software package "Surfvision", and used this software to calculate the surface parameters. Lin et al. [13] investigated the EDM process and compared GRA and fuzzy logic with Taguchi method. In [14-16], studies were conducted on surface integrity. C. L He [17] et al explored the mechanism of creation of surface roughness. Sengottuvel et al. [18] used fuzzy logic to select input parameters in EDM process and kept the tool wear, SR and MRR (material removal rate) and machining costs to a desired level.

It is observed that ample research have been performed on the surface parameters during turning, present investigation is different from the previous work with respect to the following points.

- A combined uncertainty is evaluated based on surface textures like $R_a, R_t, and\ R_z$ using Monte Carlo Simulation.
- Sensitivity analysis of the above three surface textures have been performed. Significant contributors to sensitivity are identified.

3. Most Influencing Surface Texture Parameters

Surface texture or 3D topography of a machined surface generally varies periodically or randomly from the mean surface. The description of surface texture includes roughness, waviness, lay and flaws. Geometric parameters can be categorized in two broad groups namely height parameters and spatial parameters. There are many height parameters to designate a surface. Amongst this, three height parameters which are relevant in this investigation are given hereunder.

Surface Roughness (R_a): This is the surface profile's typical height above the mean line. Such a line that divides the surface profile into two equal halves is known as the center line or mean line. Surface roughness is shown in Fig.2.

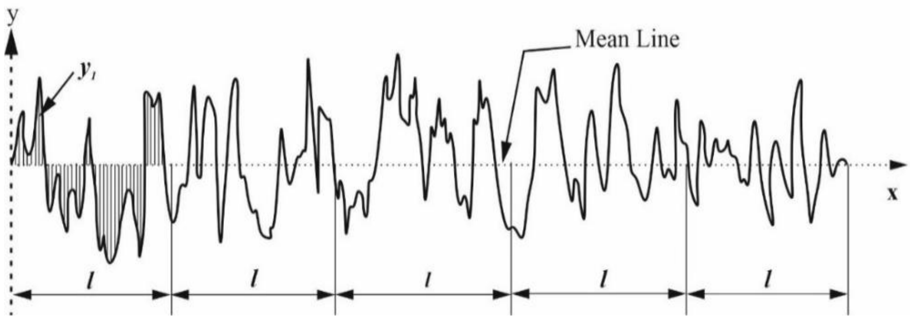


Fig.2: Pictorial view of R_a

All profile heights are measured from the reference line. Mathematically this can be written as,

$$R_a = CLA = AA = \frac{1}{L}\int_0^L |z - m|\, dx \ldots\ldots\ldots\ldots\ldots\ldots\ldots$$

$$\text{Where } m = \frac{1}{L}\int_0^L z dx$$

$$\text{Variance } \sigma^2 = \frac{1}{L}\int_0^L (z - m)^2 dx$$

The distance between the tallest peak and the deepest valley is represented by R_t . In the event of high peaks or severe scratches, this parameter is sensitive. R_t is depicted in Fig. 3.

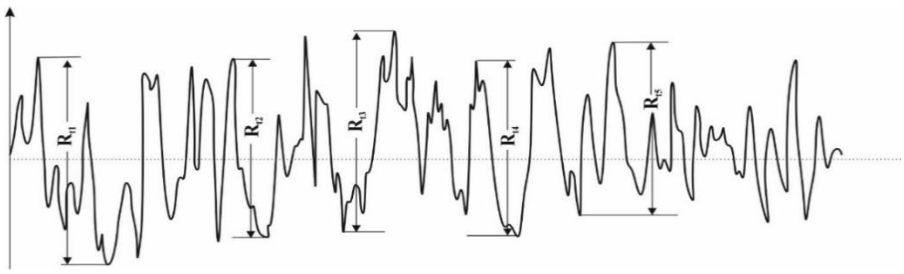


Fig.3: Pictorial view of R_t

When surfaces feature sporadic high peaks and deep valleys, R_z is more sensitive. According to the ISO standard, this is the difference between the averages of the top five peaks and the bottom five valleys, as seen in Fig. 4. This is shown mathematically in Eq. 2 as follows.

$$R_{z(ISO)} = \frac{1}{n}\sum_{i=1}^{n} p_i - \frac{1}{n}\sum_{i=1}^{n} v_i \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (2)$$

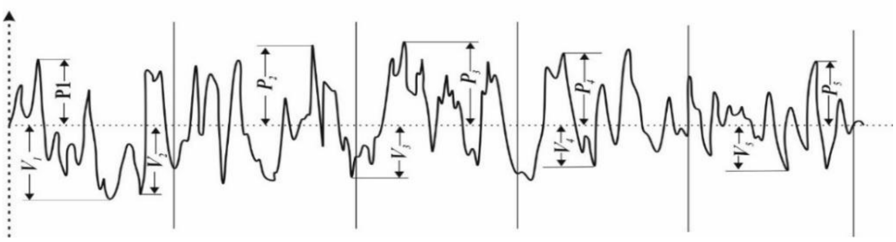


Fig.4: Pictorial view of R_z

4. Uncertainty in Manufacturing Process

Measurement is a process of assigning a value to a physical variable. But when the true value of the measurement is not known then a probable error of the measurement is determined instead of the actual error. This type of estimation is known as the uncertainty of the measured value. Uncertainty analysis is a process which is applied for quantifying & identifying the error in any measurement. In any experimental measurement, the uncertainty may arise due the systematic or bias error and random error. During a set of measurements, the systematic or bias error remains constant under the fixed working environment. This type of error can only be determined by comparison. The random error may occur due to the personal fluctuations.

5. Modelling of Uncertainty

The standard uncertainties $u_s(x_i)$ can be evaluated by two methods, Type A and Type B. Type A is basically a statistically evaluated method, based on repeated measurements. In this method, the arithmetic mean and experimental standard deviation of the mean are employed as input estimation, x_i , and the standard uncertainty $u_s(x_i)$ respectively. Type B is another method to evaluate the standard uncertainty by considering all available resources and professional experience. Though there are more than one methods to evaluate the standard uncertainties $u_s(x_i)$, there is hardly any difference between these methods for the purpose of uncertainty propagation.

5.1 Steps for modelling of uncertainty

The steps to determine and report the uncertainty of any measurement are given as follows:

a) Identify the input parameters, X_i and the responses Y for the mathematical model. The mathematical expression between the responses and input parameters are expressed as $Y = f(x_1, x_2, \dots \dots \dots, x_n)$.

b) Determine an estimate,x_i, considering the value of each input parameters, X_i.

c) Evaluate the standard uncertainty,$u_s(x_i)$, for each input estimate,x_i, by using either Type A or Type B technique of evaluation.

d) Determine the estimate, y, of the output from the relationship $y = f(x_1, x_2, \dots \dots \dots, x_n)$, where f is the function evaluated from step a.

e) Calculate the combined standard uncertainty $u_c(y)$, of the estimate y.

5.2 Determination of Standard uncertainties

As mentioned earlier, there are two methods to determine the standard uncertainties. One is Type A and another is Type B. These two methods are briefly discussed below.

5.2.1 Type A evaluations

Type A method for evaluation of standard uncertainties is based on the repeated measurements. The usual steps to evaluate the standard uncertainties by Type A method are as follows:

- Calculate the arithmetic mean, $\bar{X}_i$, which is the actual value of the input estimate, x_i and it is defined as,

$$x_i = \bar{X}_i = \frac{1}{n}\sum_{k=1}^{n} X_{i,k} \quad (1)$$

Where,

X_i is the input parameter in the mathematical model.

n denotes the number of experiments which have done under the same working conditions.

- Determine the experimental standard deviation, $s(X_{i,k})$ of data obtained from experimentation value and it is defined as,

$$s(X_{i,k}) = \sqrt{\frac{1}{(n-1)}\sum_{k=1}^{n}\left(X_{i,k} - \bar{X}_i\right)^2} \quad (2)$$

- Evaluated the experimental standard deviation of mean $s(\bar{X}_i)$ and this can be calculated by dividing $s(X_{i,k})$ by $\sqrt{n}$.

$$s(\bar{X}_i) = \frac{s(X_{i,k})}{\sqrt{n}} \quad (3)$$

The experimental standard deviation of mean is also called the standard uncertainty, $u_s(x_i)$. Therefore the standard uncertainty, $u_s(x_i)$ is expressed as

$$u_s(x_i) = \sqrt{\frac{1}{n(n-1)} \sum_{k=1}^{n} \left(X_{i,k} - \bar{X}_i\right)^2} \qquad (4)$$

5.2.2 Type B evaluations

The evaluation of standard uncertainty by using Type B method is done considering all available resources and scientific judgment. The steps for evaluating the standard uncertainty by Type B is given as follows:

- Calculation of the input estimate,x_i using the following expression,

$$x_i = \frac{(a^+ + a^-)}{2} \qquad (5)$$

Where, $a^+ and\ a^-$ are the upper limit and lower limit of the probability distribution respectively.

- Evaluated the standard uncertainty, $u_s(x_i)$.

In all most all cases the standard uncertainty is computed using the rectangular probability distribution and the expression of standard uncertainty $u_s(x_i)$ is given as,

$$u_s(x_i) = \frac{a}{\sqrt{3}} \qquad (6)$$

Where,

$$a = \frac{(a^+ - a^-)}{2}$$

If the distribution employed to the model is triangular instead of rectangular, the standard uncertainty $u_s(x_i)$ becomes,

$$u_s(x_i) = \frac{a}{\sqrt{6}} \qquad (7)$$

5.3 Evaluation of Combined uncertainty

The combined standard uncertainty is denoted as $u_c(y)$ and it is calculate using the following expression,

$$u_c{}^2(y) = \sum_{i=1}^{n} \left(\frac{\partial f}{\partial x_i}\right)^2 u_s{}^2(x_i) + \ 2\sum_{i=1}^{n-1} \sum_{j=i+1}^{n} \frac{\partial f}{\partial x_i} \frac{\partial f}{\partial x_j} u\left(x_i, x_j\right) \qquad (8)$$

The above expression is also called the law of propagation of uncertainty.

Where,

$u_s{}^2(x_i)$ is designated as the estimated variance of x_i.

$u\left(x_i, x_j\right)$ represents the estimated covariance related with $x_i\ and x_j$.

$\frac{\partial f}{\partial x_j}$ is denoted as sensitivity coefficients.

$u_c{}^2(y)$ is denoted as the combined variance of y.

$u_c(y)$ represents the combined uncertainty.

When the input estimate, $x_1, x_2, \dots \dots \dots, x_n$ are not correlated then the equation (8) becomes,

$$u_c{}^2(y) = \sum_{i=1}^{n} \left(\frac{\partial f}{\partial x_i}\right)^2 u_s{}^2(x_i) \qquad (9)$$

with respect to actual data.

6. Monte Carlo Simulation (MCS)

MCS is a statistical tool used to incorporate risk and uncertainty in a model which helps to visualize most or all of the potential outcomes to have a better idea of uncertainty of a model. The Monte Carlo Simulation considers probability distribution in order to design a random or a stochastic factor. Various probability distributions are applied for designing input factors such as uniform, lognormal, normal, and triangular. The probability distribution obtained from the input factor, different paths of outcome are generated. MCS method includes the following steps:

- Specify the range and type of distribution for each input parameter.
- Create a random dataset from the input parameters
- Distribution of the dataset through the mathematical model under evaluation.
- Simulation of uncertainty analysis.

Global sensitivity analysis is an alternative method of sensitivity analysis and is implemented with MCS. This technique applies global set of combination of input variables to explore the design space. Following three methods are generally applied to perform sensitivity analysis.

1. *Measurement of sensitivity considering one parameter:* This is the most fundamental method which uses partial derivatives where only one input parameter is considered at a time. It is considered local analysis in the sense that only one-point estimate is considered and not entire gamut of distribution.
2. *Differential sensitivity analysis :* This technique is the most-straight forward. It involves a solution of simple partial derivatives. Although this is computationally efficient, more often it creates an intensive task to solve the equation of partial derivatives.
3. *Sensitivity analysis with factorial :* In this method, first a given no. of samples of a specific parameter are selected, then the model is run with different combinations. The outcomes are studied to carry out parameter sensitivity.

Sensitivity index is defined as the difference in % output when a single input parameter varies from minimum to maximum value. Following techniques are used to perform sensitivity analysis.

- Correlation analysis is used to establish the relation between independent and dependent variables
- Regression analysis is used generally to get a response for complex models.
- Subjective sensitivity analysis is used to analyses the input parameter. This method is subjective in the sense, it is simple, qualitative and easy to rule out input parameters.

Fig.5 indicates how uncertainty and sensitivity influences each other.

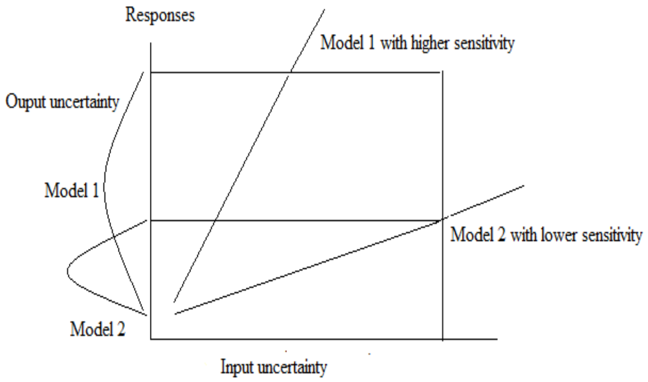


Fig.5: Relation between uncertainty and sensitivity

7. Experimentation

7.1 Machineries:

In the present work, MTAB MAXTURN PLUS CNC turning centre is used for dry turning operation. It is a 2-axis production machine with 8 stations programmable turret and BTP 50 tools. The experimental setup is demonstrated in Fig.6.

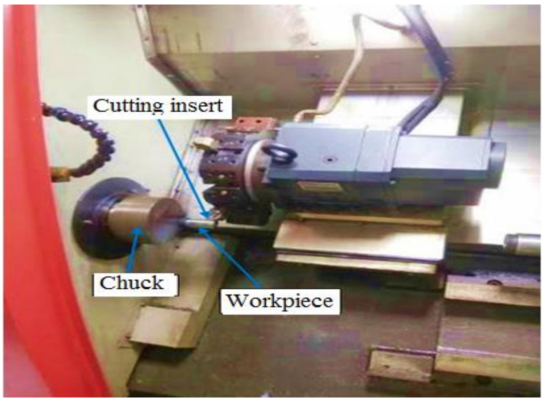


Fig.6: Dry turning operation in CNC Turning Centre

7.2 Measuring instruments:

Surface parameters are measured by Surface Roughness Tester SJ-410 series of Mitutoyo. The Surface Roughness Tester is shown in Fig.7.

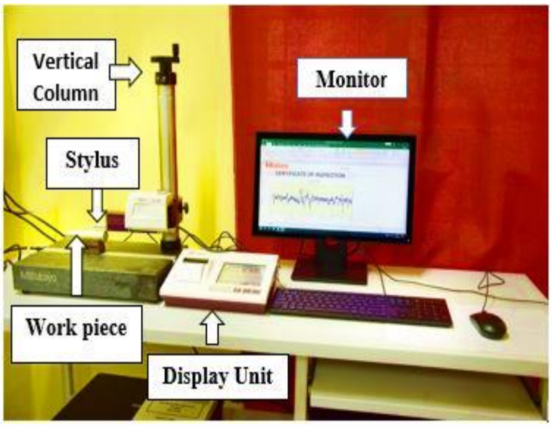


Fig.7: Measurement of surface textures

7.3 Work piece:

In the present work, AISI 4140 alloy steel is taken as work piece material. The diameter of the work piece is 25 mm and the length of this is 150 mm. The chemical composition of AISI4140 is shown in Table 1.

Table 1: Chemical Composition of AISI 4140

Mn	Si	Cr	C
0.85	0.22.2	0.90	0.402

7.4 Cutting tool:

Coated carbide tool Grade T9115 is used to perform the experiments and CNMG 12-04-08 type of insert is used. T-type tool holder is used to hold the tool insert. The cross section of the holder is squared type having height and width of 20 mm.

7.5 Process Variables and their Limits:

Using Mini Tab 17 software and the variables and their bounds, an experiment's design has been carried out in accordance with RSM. Central composite face-centered design (CCD) is used to decide how many tests to run and how to combine the input parameters. Spindle speed, feed rate, and depth of cut are the input cutting parameters; they are designated as A, B, and C, respectively, and their ranges are displayed in Table 2.

Table 2: Variables and their levels

Cutting parameters	Code	Level 1	Level 2	Level 3
		-1	0	1
Spindle speed (m/min)	A	80	120	150
Feed(mm/min)	B	0.1	0.2	0.3
Depth of cut (mm)	C	0.1	0.2	0.3

8. Results and Discussions

This inquiry uses AISI4140 alloy steel as the work piece material in 27 experiments that are carried out in a dry environment on a CNC machine. Cutting tools are coated carbide tools. Based on the material qualities, prior study, and capacity of the available machining set up, the input parameter ranges for speed, feed, and depth of cut are chosen. A surface roughness tester is used to measure the surface height parameters like R_a, R_z, R_t, and the results are displayed in Table 3. These variables are all expressed in millimeters. All of these values are seen to be randomly distributed and lack any discernible pattern.

Table 3: Responses with combination of input parameters

Sl. No.	Input parameters			Surface texture parameters		
	Speed	Feed	Depth of cut	R_a	R_z	R_t
1	80	0.3	0.1	3.78	13.86	11.23
2	80	0.3	0.3	3.98	12.65	12.37
3	120	0.2	0.3	4.11	17.88	12.5
4	80	0.1	0.3	3.4	15.55	14.17
5	80	0.2	0.2	3.62	14.06	13.02
6	150	0.1	0.2	3.64	11.24	11.95
7	150	0.2	0.1	3.7	11.88	11.79
8	150	0.1	0.1	3.48	10.86	12
9	120	0.2	0.2	4.05	14.48	13.76
10	80	0.2	0.3	3.84	15.08	14.87
11	150	0.2	0.2	3.34	13.16	13.89
12	150	0.3	0.3	4.05	14.42	17.04
13	120	0.1	0.3	3.86	14.83	13.52
14	80	0.1	0.1	3.24	13.24	11.86
15	120	0.1	0.2	3.68	12.74	11.54
16	150	0.1	0.3	3.73	13.64	13.87
17	150	0.3	0.1	4.01	12.88	12.76
18	120	0.3	0.2	4.24	12.08	14.54
19	120	0.2	0.1	3.84	13.45	11.86
20	120	0.3	0.1	3.96	14.18	12.83
21	80	0.2	0.1	3.84	12.11	11.53
22	150	0.3	0.1	3.98	13.21	14.01
23	80	0.1	0.2	3.91	11.01	11.78
24	80	0.3	0.2	4.01	14.12	12.58
25	150	0.3	0.2	4.06	13.98	13.52
26	120	0.1	0.1	3.99	11.15	11.12
27	150	0.2	0.3	4.12	13.58	13.68

Since main objective of this investigation is to find out the uncertainty and sensitivity of the models developed by widely used Response Surface Methodology (RSM) as per the current available literature. Three regression models using Response Surface Methodology (RSM) are developed for R_a , and $R_z, and\ R_t$ and are shown in Eq. 11, Eq. 12, and Eq. 13 using Minitab version 17. Fig.8 shows the distribution of the errors obtained from the model. This error or residual is defined as the deviation of the model value from the experimental value.

R_a = 1.19 + 0.0438 S + 0.17 F - 0.84 D - 0.000194 S×S + 2.81 F×F + 1.31 D×D + 0.0025 S×F + 0.0063 S×D + 2.01 F×D……………………….(11)

R_z = 3.93 + 0.1150 S + 36.0 F - 10.3 D - 0.000684 S×S - 77.6 F×F + 69.2 D×D + 0.1115 S×F + 0.0527 S×D - 65.2 F×D……………………….(12)

R_t = 14.88 - 0.0581 S - 16.7 F + 6.7 D + 0.000130 S×S + 0.1 F×F + 5.5 D×D + 0.1883 S×F + 0.0130 S×D + 1.6 F×D……………………….(13)

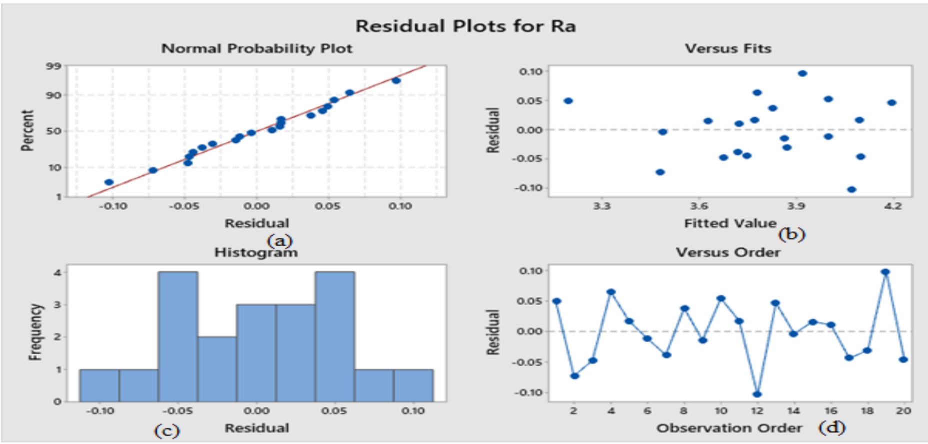
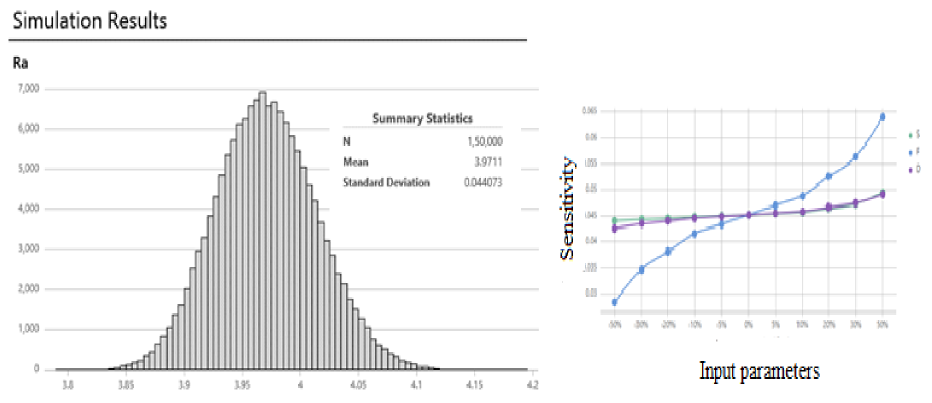


Fig.8: Residual Plots for Surface Roughness, R_a (μm). (a) shows the normal probability plot of the residuals, (b) indicates residual Vs the best fit value (c) shows the histogram of residual distribution and (d) shows individual residual for each observation.

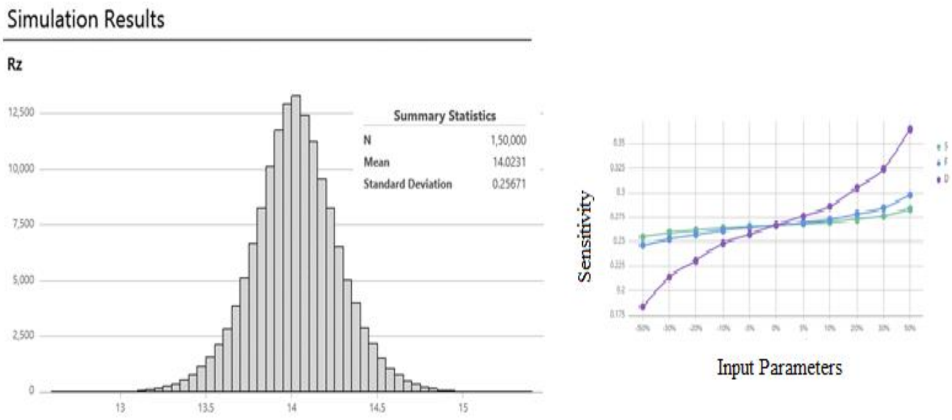
Fig.9 (a) indicates the probability distribution function (PDF) of the normal probability plot of R_a shown in Fig.8 (a). It estimates the uncertainty (standard deviation) of R_a as 0.0440. Fig.9 (b) shows that feed (F) is the most sensitive parameter in the model of R_a. Therefore, it can be stated that feed (F) also incorporates most uncertainty in the model as per Fig.5. Speed and depth of cut incorporate very low uncertainty and sensitivity in the model as per Fig.9 (b).



(a) (b)

Fig. 9: Uncertainty (a) and sensitivity (a) of R_a

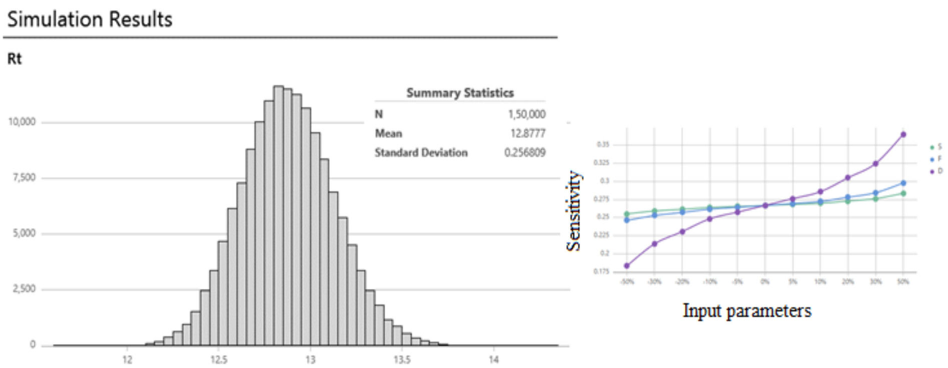
Fig.10 (a) indicates the probability distribution function (PDF) of the normal probability plot of R_z. It estimates the uncertainty (standard deviation) of R_z as 0.2567. Fig.10 (b) shows that depth of cut (D) is the most sensitive parameter in the model of R_z. Therefore, it can be stated that depth of cut (D) also incorporates most uncertainty in the model as per Fig. 5. Speed and feed incorporate low (but more than in R_a) uncertainty and sensitivity in the model as per Fig.10 (b).



(a) (b)

Fig.10: Uncertainty (a) and sensitivity (a) of R_z

Fig.11(a) indicates the probability distribution function (PDF) of the normal probability plot of R_t. It estimates the uncertainty (standard deviation) of R_t as 0.2568. Fig.11(b) shows that depth of cut (D) is the most sensitive parameter in the model of R_t. Therefore, it can be stated that depth of cut (D) also incorporates most uncertainty in the model as per Fig. 6. Speed and feed incorporate low (but more than in R_a) uncertainty and sensitivity in the model as per Fig.11(b).



(a) (b)

Fig.11 Uncertainty (a) and sensitivity (a) of R_t

Table 4 indicates a summary of mean and uncertainty of the three surface textures under investigation.

Table 4: Summary of uncertainties of surface textures

Responses	No. of iterations	Mean	Uncertainty
R_a	150000	3.971	0.044
R_z	150000	14.023	0.256
R_t	150000	12.877	0.256

9. Conclusions

In this investigation, uncertainties and sensitivities of the statistical models obtained from RSM of three surface textures are analyzed. AISI4140 alloy steel and carbide tools are considered as workpiece and cutting tools respectively. The best surface in terms of minimum value of R_a, R_z *and* R_t has been determined. Objective weights of the responses are determined with PCA. Significant observations of this investigation are as follows.

- Uncertainty of the model of R_a is 0.0440. The feed is identified as the most significant contributor to uncertainty. The sensitivity of the model of R_a has been performed and feed is also identified as the most sensitive parameter.
- Uncertainty of the model of R_z is 0.2567. The speed is identified as the most significant contributor to uncertainty. Sensitivity of the model of R_z has been performed and speed is also identified as the most sensitive parameter.
- Uncertainty of the model of R_t is 0.2568. The speed is identified as the most significant contributor in uncertainty. Sensitivity of the model of R_z has been performed and speed is also identified as the most sensitive parameter.

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