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ARTICLE



# A new approach to explore tool chatter in turning operation on lathe

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**ABSTRACT**
Tool chatter is an ineluctable phenomenon encountered frequently in turning process. In the present work, statistical approach along with signal pre-processing has been adopted to explore the mechanism of tool chatter in turning operation. Experiments have been performed to acquire raw chatter signals. Wavelet transforms have been used for pre-processing these signals in order to remove the ambient noise contents. Further, response surface methodology (RSM) has been adopted to develop quadratic and cubic mathematical models of tool chatter considering three cutting parameters: depth of cut (*d*), feed (*f*) and spindle speed (*N*). In order to examine the influence of aforesaid cutting parameters on chatter severity, a new parameter called chatter index has been evaluated. Moreover, analysis of variance has been performed to check the statistical significance and combined effect of control parameters on machined output. The results have been analysed using regression plots and 3D surface graphs. More experiments have been conducted to validate the developed model. Well correlation between the predicted and experimental results validates the developed technique of ascertaining the tool chatter severity.

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**KEYWORDS**
Wavelet de-noising; chatter; response surface methodology

## 1. Introduction

Tool chatter is defined as self-induced relative vibration produced at the interface of tool and workpiece in conventional machining processes such as turning. This phenomenon affects the product quality, wastage of workpiece material and increased production time. In the present scenario, chatter exploration and mitigation is one of the challenging tasks (Quintana and Ciurana 2011; Siddhpura and Paurobally 2012). In the last decade, researchers have suggested various methods such as parametric excitation (Yao, Mei, and Chen 2011), use of passive adaptor (Anderson, Semercigil, and Turan 2007), piezoelectric actuation (Albizuri et al. 2007), active structural control (Dohner et al. 2004) and use of magnetic bearing (Chen and Knospe 2007) in order to suppress tool chatter. Recently, some researchers have adopted spindle speed variation technique (Wu and Chen 2010; Otto and Radons 2013; Hajikolaei et al. 2010) and use of multiple tuned mass damper (Yang, Munoa, and Altintas 2010) to mitigate the chatter effect. Mechanism of tool chatter has also been presented mathematically by some researchers in linear and non-linear forms (Hajikolaei et al. 2010; Chandiramani and Pothala 2006; Dassanayake and Suh 2008). In the past, it has been established by the researchers that depth of cut, feed rate, cutting speed and spindle speed are the dominant cutting parameters affecting chatter phenomenon. However, till date, no mathematical expression of tool chatter severity in terms of aforesaid parameters has been developed. Clancy and Shin (2002) observed that chatter can be minimised to a great extent by reducing the depth of cut and feed rate. They also concluded that the cutting stability is enhanced at low cutting speed. Moreover, apart from aforesaid cutting parameters, some researchers have found that cutting forces also affect the chatter phenomenon. Tangjitsitcharoen (2009) have suggested that cutting force components influence the chatter the phenomenon and are responsible for continuous and broken chip formation. They also suggested that broken chip formation is safe and reliable for machining. Altintas and Weck (2004) established that the dynamic cutting force not only depends on chip thickness but also on the shear angle oscillation and tool flank wavy surface contact mechanism.

Moreover, some researchers have tried to explore the mechanism of tool chatter by processing the acquired raw tool chatter signals. Recently, signal processing techniques such as Fourier transforms (FTs) and short-time Fourier transforms (STFTs) have been used by the researchers to study the process of tool chatter (Bayly et al. 2001; Sastry, Kapoor, and DeVor 2002; Tansel et al. 2006). Further, because of certain shortcomings in aforesaid techniques, wavelet transform (WT) technique came into picture (Taylor, Turner, and Sims 2010; Yao, Mei, and Chen 2010). In comparison to FT and STFT, WT possesses have certain advantages such as performing local analysis, handling both stationary and non-stationary signals and also providing efficient time-frequency analysis (Wang and Liang 2009). In the present work, WT has been adopted to pre-process the raw chatter signal by de-noising it, in order to eliminate the ambient noise contents embedded in the signal.

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Furthermore, chatter phenomenon results in poor surface finish of the workpiece. In order to improve the product quality, it is necessary to reduce surface roughness by suppressing tool chatter. Many researchers have adopted various statistical approaches to predict the surface roughness of workpiece in turning operation. Hashmi et al. (2016) proposed a mathematical model of surface roughness in terms of depth of cut, feed and cutting speed. They observed that surface roughness of machined workpiece is mainly influenced by depth of cut. Sarıkaya and Gullu (2014) developed a model of surface roughness using response surface methodology (RSM) considering cutting speed, feed rate and depth of cut as cutting parameters. In their study, they concluded that the given model is well suited for turning of AISI 1050 steel. Bouacha et al. (2010) have proposed a mathematical model for surface roughness considering RSM. They observed that feed rate and cutting speed influence the surface roughness more in comparison to other cutting parameters. Moreover, RSMs have also been employed by many researchers to evaluate the surface roughness of the fabricated and assembled structures (Singh and Nanda 2012a, 2012b).

In the present work, RSM has been adopted to develop mathematical model of chatter severity in terms of depth of cut, feed and cutting speed. Outline of the present work is as follows: first, experimentally recorded raw chatter signals have been de-noised using WT technique and thereby a new parameter denoted as chatter index (CI) has been evaluated. Second, RSM has been used for developing quadratic and cubic models. Analysis of variance (ANOVA) has been carried out to check the statistical significance of cutting parameters. Finally, more number of experiments has been conducted and experimental readings have been compared with the predicted ones to validate the developed model.

## 2. Theoretical background of chatter mechanism

In the present work, a single degree of freedom (SDoF) turning operation with a flexible tool and rigid workpiece has been considered as shown in Figure 1. Mathematical model for turning operation has been represented by SDoF equation (Siddhpura and Paurobally 2012; Zhang, Wang, and Liu 2012):

$$m\ddot{q}(t) + c\dot{q}(t) + kq(t) = F_{\mathrm{f}}(t) \tag{1}$$

where $F_{\mathrm{f}}(t)$ is the dynamic cutting force in feed direction, $m$ is the mass of tool, $c$ represents the damping coefficient and $k$ is the stiffness.

Equation (1) has been further written as

$$\ddot{q}(t) + \frac{c}{m}\dot{q}(t) + \frac{k}{m}q(t) = \frac{1}{m}F_{\mathrm{f}}(t) \tag{2}$$

$F_{\mathrm{f}}(t)$ is given by

$$F_{\mathrm{f}}(t) = k_{\mathrm{f}} \times b \times d(t) = k_{\mathrm{f}}b[d_0 + q(t-\tau) - q(t)] \tag{3}$$

where $b$ is the chip width, $k_{\mathrm{f}}$ is the cutting force coefficient, $d_0$ is nominal chip thickness and $\tau$ is the time delay between current time and previous time. Here, $\tau = \frac{60}{N}$, $N$ is the spindle speed in rpm.

In above equation $d(t)$ is the dynamic chip thickness due to tool vibration and is equal to $[d_0 + q(t-\tau) - q(t)]$

For apparent understanding, a framework of the proposed chatter detection has been shown in Figure 2.

## 3. Experimental procedure

In order to study the chatter mechanism, turning operation has been performed on ASTM A36 mild steel by using high-speed precision lathe NH22 (Hindustan Machine Tool Ltd.). During turning operation, an accelerometer is mounted on the bearing seal of chuck. Further, data acquisition system has been attached to accelerometer in order to acquire the chatter signal for each experiment. The experiments have been conducted with different set of cutting parameters ($d$, $f$ and $N$) as

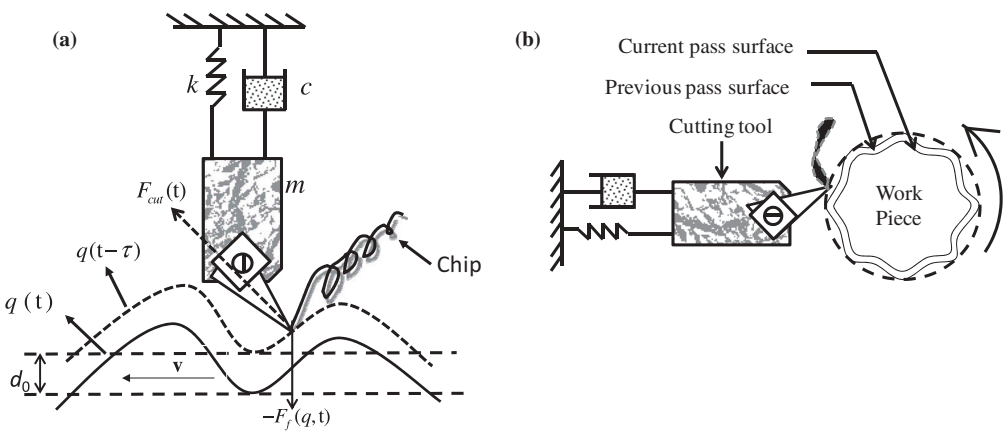


Figure 1. (a) Mechanism of regeneration and (b) SDoF model for turning.

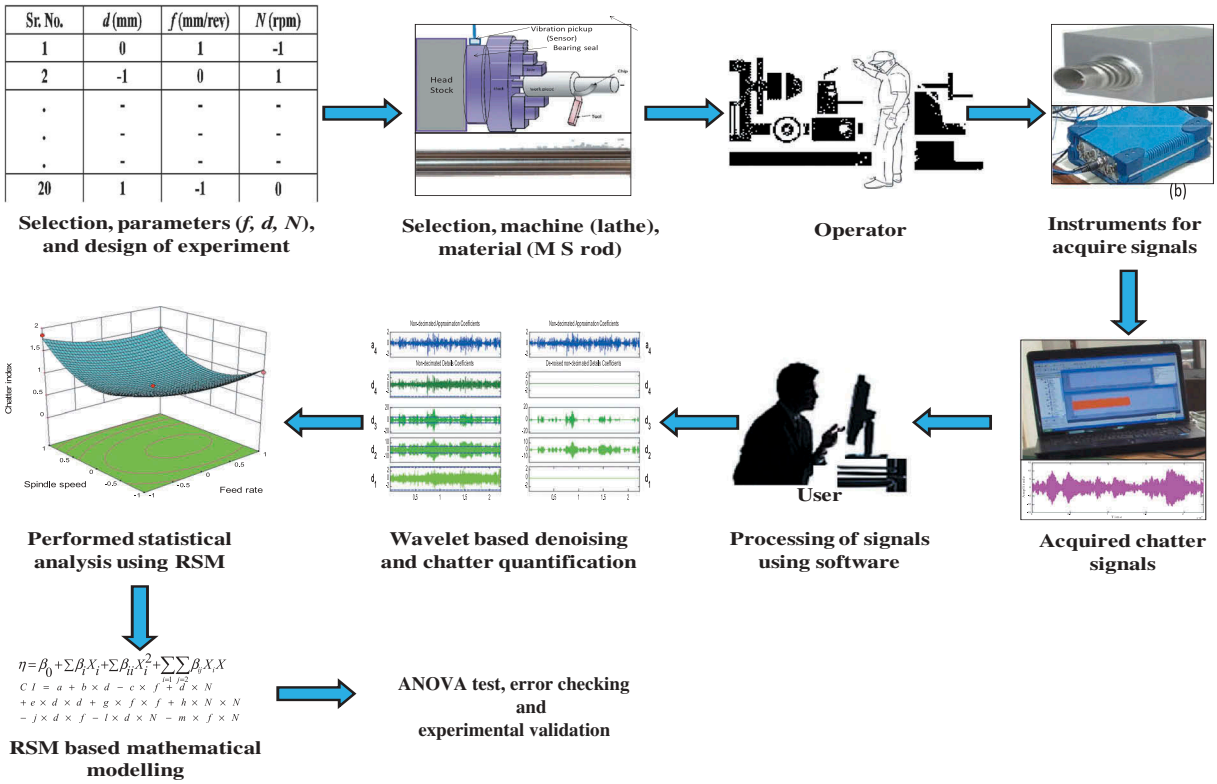


Figure 2. Flow chart of proposed methodology.

shown in Figure 3. Schematic diagram of the experimental set-up has been presented in Figure 3. Figure 4 shows the experimental set-up.

### 3.1. Tool and equipment

A single point cutting carbide tool has been used for turning of mild steel bars. An accelerometer (Make: PCB PIEZOTRONICS and Model: 356A16) mounted on the bearing seal of chuck and data acquisition system (Make: OROS group and Model: OR35-multi analyser) has been used to acquire the raw chatter vibration signals which has been shown in Figure 5(a,b), respectively.

### 3.2. Work material

In the present investigation, ASTM A36 mild steel has been used as a workpiece material for turning operation. Chemical composition of workpiece has been listed in Table 1. For each set of turning, a

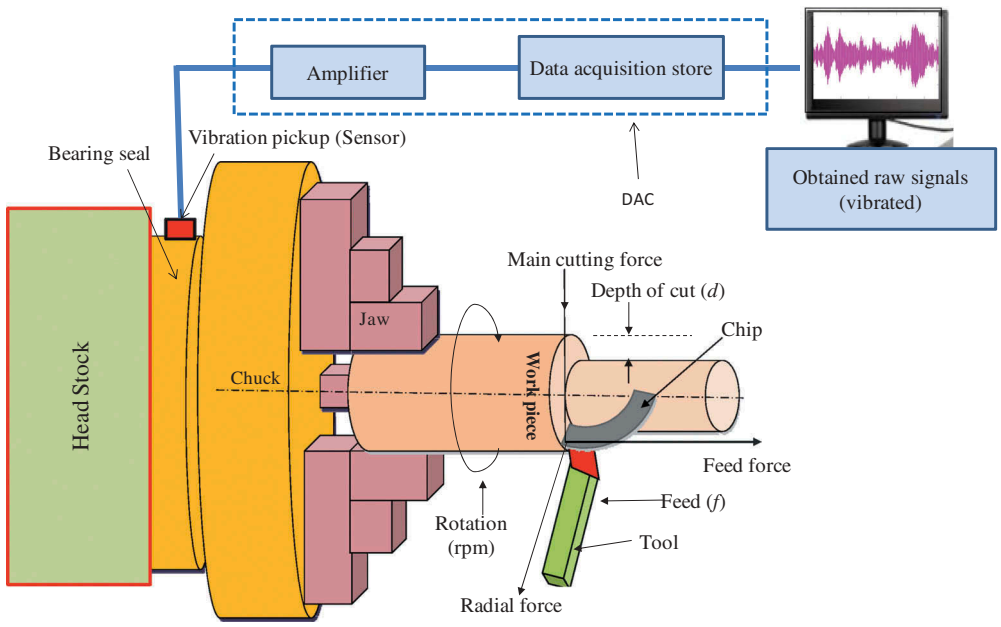


Figure 3. Schematic diagram of experimental set-up.

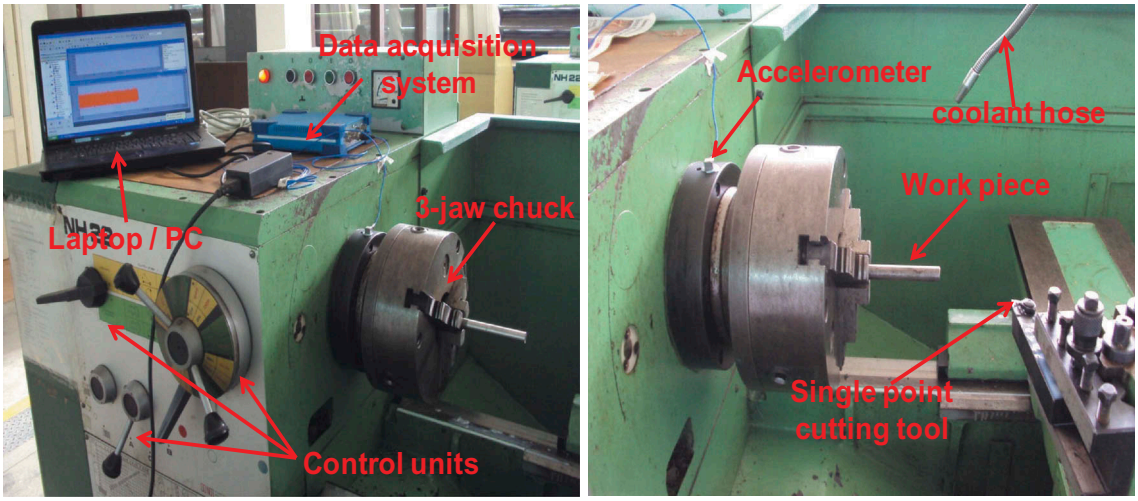


**Figure 4.** Experimental set-up.

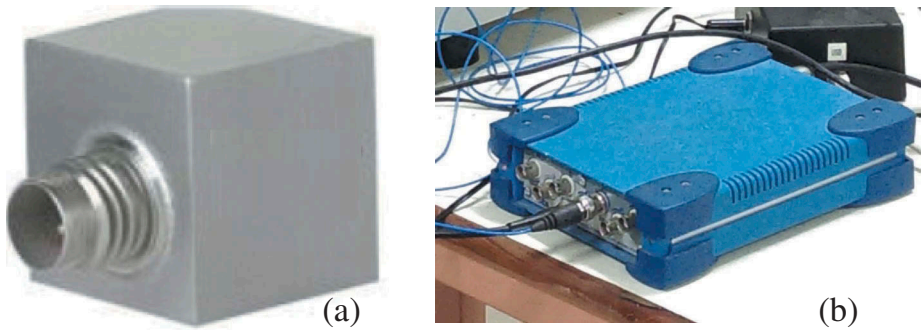


**Figure 5.** (a) Accelerometer and (b) data acquisition system (multi-analyser).

**Table 2.** Control factors and their levels.

| Sr. no. | Symbol | Factor | Unit | Level 1 | Level 2 | Level 4 |
|---|---|---|---|---|---|---|
| 1 | *d* | Depth of cut | mm | 0.5 | 1.5 | 2.5 |
| 2 | *f* | Feed rate | mm/rev | 0.05 | 0.15 | 0.25 |
| 3 | *N* | Spindle speed | rpm | 700 | 1000 | 1300 |

new bar of work material has been used. Workpiece of 200 mm length and 40 mm diameter has been used as shown in Figure 6. Here, 140 mm length of workpiece has been used for turning while remaining 60 mm length was used for holding purpose in chuck.

**Table 1.** Chemical composition of work material (A36 mild steel bar).

| | | | |
|---|---|---|---|
| C | 0.25–0.290% | P | 0.040% |
| Cu | 0.20% | Si | 0.280% |
| Fe | 98.0% | S | 0.050% |
| Mn | 1.03% | | |

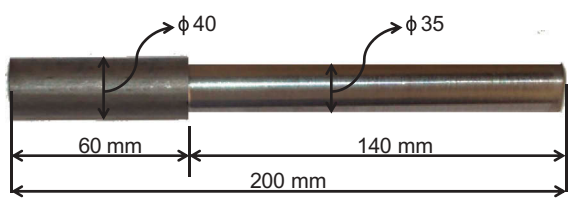


**Figure 6.** Workpiece sample.

### 3.3. Cutting parameters and levels

In the present study, three cutting parameters depth of cut (*d*), feed rate (*f*) and spindle speed (*N*) have been considered for experimentation and each parameter has three levels as shown in Table 2. Here, experimental runs have been designed using central composite designs (CCDs), which gives 20 experimental runs.

Moreover, considering different set of aforesaid cutting parameters, signals have been acquired experimentally. Further, acquired signals have been pre-processed using wavelet de-noising technique in order to obtained accurate and smooth results.

## 4. De-noising using WT

The inclusion of noise in the signal interrupts the identification of exact chatter. Several approaches such as kernel estimators, spline estimators and Fourier-based signal processing have been considered by different researchers. But these techniques have certain limitations and inaccuracies. Therefore, more appropriate novel approach is required for de-noising, which motivated this research. In this study, wavelet de-noising technique has been done. In wavelet de-noising technique, the noisy signal is first decomposed using WT, where the level of decomposition depends upon the

length of the signal. After decomposition, the thresholding of the coefficients has been done. If the wavelet coefficient is smaller than the threshold level, it is then set as zero and if the coefficient is larger than threshold level, it is either adapted or kept as it is.

### 4.1. Wavelet decomposition

The aforesaid de-noising technique has been implemented in two steps i.e. wavelet decomposition and wavelet thresholding. In wavelet decomposition technique, the acquired signal of finite energy is passed through low-pass and high-pass filter. Low-pass filter will result in approximate coefficient while high-pass filter will yield detailed coefficient. The methodology of signal decomposition has been shown in Figure 7.

The selection of decomposition level depends on the length of the signal ($n$). The length of signal should be completely divisible by 2^level. For example, if $n$ = 1008, the maximum possible decomposition level can be 4, as 2 to the power 4 ($2^4$) is equal to 16 and 1008 is completely divisible by 16. So, in the present work, decomposition level '4' has been considered to reduce computing time and enhance chatter responsiveness.

### 4.2. Wavelet thresholding

Generally, hard or soft thresholding rules have been adopted for de-noising purpose. If the wavelet coefficient values are greater than the given threshold level, then hard thresholding function will retain all wavelet coefficients above threshold level and rest are set as zero (Debnath 2003). Hard thresholding is defined as

$$W_{T\_H} = \begin{cases} W & |W| \geq T \\ 0 & |W| < T \end{cases} \tag{4}$$

where $W$ is the noisy wavelet coefficient and $T$ is the threshold.

In soft thresholding, if the wavelet coefficient values are greater than given threshold, then soft thresholding function shrinks the wavelet coefficient and the rest are set as zero (Debnath 2003). Soft thresholding is defined as

$$W_{T\_S} = \begin{cases} W - T & \mathrm{W} \geq T \\ 0 & |W| < T \\ W + T & \mathrm{W} \leq -T \end{cases} \tag{5}$$

However, hard thresholding is based on keep or remove approach; hence, it classifies a true signal as noise and vice versa. On the other hand, soft thresholding shrinks the wavelet coefficients. Due to these difficulties, both the rules are unable to de-noise the signal accurately and may leave the chatter undetected. In order to overcome the limitations of the aforesaid thresholding methods, an adaptive hybrid thresholding approach has been adopted (Wang and Liang 2009) and is given by

$$W_T = \begin{cases} W - \mathrm{sgn}(W)(1 - \zeta) \times T & |W| \geq T \\ 0 & |W| < T \end{cases} \tag{6}$$

Here, $\zeta$ is a parameter in the range of (0, 1) and $T$ is the thresholding level given by

$$T = \sigma\sqrt{2\log(n)} \tag{7}$$

where $n$ is the length of signal and $\sigma$ is the standard deviation of noise.

## 5. Experimental results for CI

Cutting parameters play a prominent role in producing chatter in turning process. Several researchers have investigated the effect of cutting parameters on chatter in turning operation, but their investigation was based on raw signals. These raw signals are contaminated with noisy signals. Hence, their results on chatter identification were not so much accurate. Till date, no work has been reported yet, on investigation

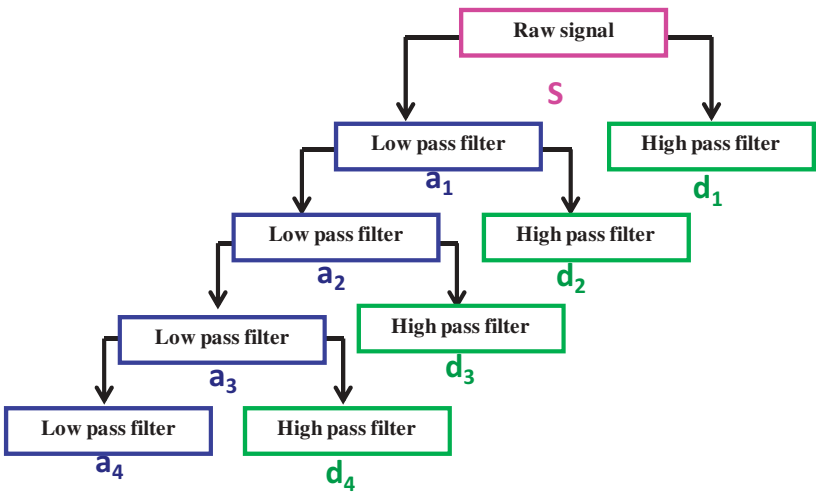


Figure 7. Wavelet decomposition of signals.

of chatter information considering the de-noised signals. In the present work, chatter severity has been explored by evaluating a new parameter called CI.

CI has been evaluated using the given relation:

$$CI = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(x_i - \mu)^2} \tag{8}$$

where CI is the chatter index, $n$ is the length of signal and $\mu$ is the mean. '$X_i$' represents the amplitude of chatter vibration at different time instances.

In turning operation, CI indicates the prominence of particular set of parameters in generating chatter. Higher the value of CI, more will be the resultant chatter. Thus, CI helps in identifying the severity of chatter.

## 6. RSM

### 6.1. Overview and methodology

In the present work, RSM has been used as a prediction methodology and is used to get the optimum value of the given responses. Individual and combined effect of input parameters $d$, $f$ and $N$ on CI can be easily predicted with the help of RSM. RSM has been implemented to find out the relationship between responses and cutting parameters. RSM is generally defined as a statistical regression method employing mathematical relations (Montgomery 2009). The objective of this technique is to correlate the response with various independent input variables influencing it.

The mathematical relation between input and output variables in RSM is generally expressed in the form of second-order polynomial expression as given by

$$\eta = \beta_o + \beta_1 x + \beta_2 y + \beta_3 z + \beta_4 x^2 + \beta_5 y^2 + \beta_6 z^2 + \beta_7 xy + \beta_8 xz + \beta_9 yz \tag{9}$$

A cubic mathematical relation between input and output variables in RSM is generally expressed as

$$\eta = \beta_o + \beta_1 x + \beta_2 y + \beta_3 z + \beta_4 xy + \beta_5 xz + \beta_6 yz + \beta_7 x^2 + \beta_8 y^2 + \beta_9 z^2 + \beta_{10} xyz + \beta_{11} x^2 y + \beta_{12} x^2 z + \beta_{13} xy^2 + \beta_{14} xz^2 + \beta_{15} y^2 z + \beta_{16} yz^2 + \beta_{17} x^3 + \beta_{18} y^3 + \beta_{19} z^3 \tag{10}$$

where $\eta$ is response (CI), $x$, $y$ and z are independent variables and $\beta_o$, $\beta_1 \ldots$ to $\ldots \beta_{19}$ are known as parameters of approximation function.

### 6.2. CCD

For applying RSM, it is necessary to select proper cutting parameters and their range. Experimental design is the process of selecting minimum combination of control parameters affecting a particular process. It involves minimum number of experiments, less time and material consumption. In present study, design of experiment has been performed using three factor three levels CCD and regression technique with ANOVA test for evaluating the performance of model.

The graphical representation of three factors CCD in the form of cube has been shown in Figure 8. It has total '20' runs consisting of '6' centre points and '14' non-centre ('8' factorial and '6' axial) points. Moreover, during experimental design, replications of factorial and axial points have been fixed at '1' while face centre is considered at '1' $(\alpha = 1)$ .

## 7. Results and discussion

### 7.1. Signal acquisition and pre-processing

Experiments have been performed in order to acquire the raw chatter signals and some of the recorded signals have been shown in Figures 9–11. These recorded raw signals have severe noise inclusions and further pre-processed by wavelet de-noising.

In the present study, wavelet de-noising has been done using MATLAB software to acquire de-noised signals as shown in Figures 12–14. In Figures 12–14, $d_1$, $d_2$, $d_3$ and $d_4$ are stationary detailed coefficients acquired at decomposition levels 1, 2, 3 and 4, respectively. A detailed coefficient has been obtained when raw signal is passed through high-pass filter, while approximated coefficient '$a_4$' has been obtained at lower frequency.

Moreover, in order to explore chatter severity, a new parameter called CI has been evaluated considering aforesaid de-noised signals. The absolute values of CI obtained using Equation (8) at different set of cutting parameters in coded form have been shown in Table 3. Here, the coded values are in the range of −1 to +1. The transformation of uncoded variables into coded form is done by using the given relation:

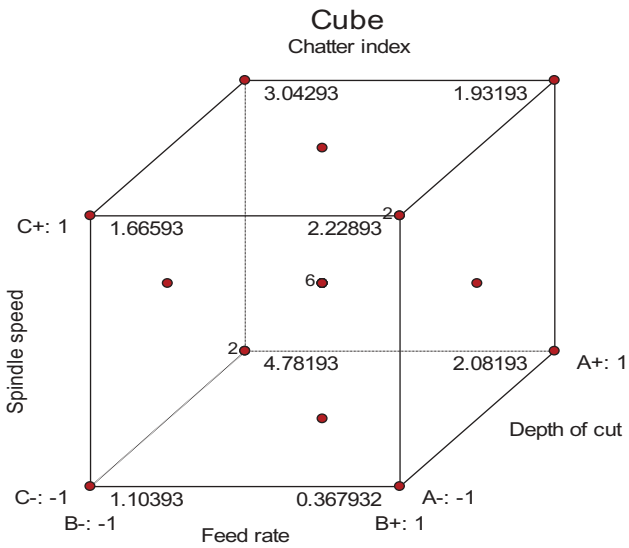


Figure 8. Central composite design space cube for CI.

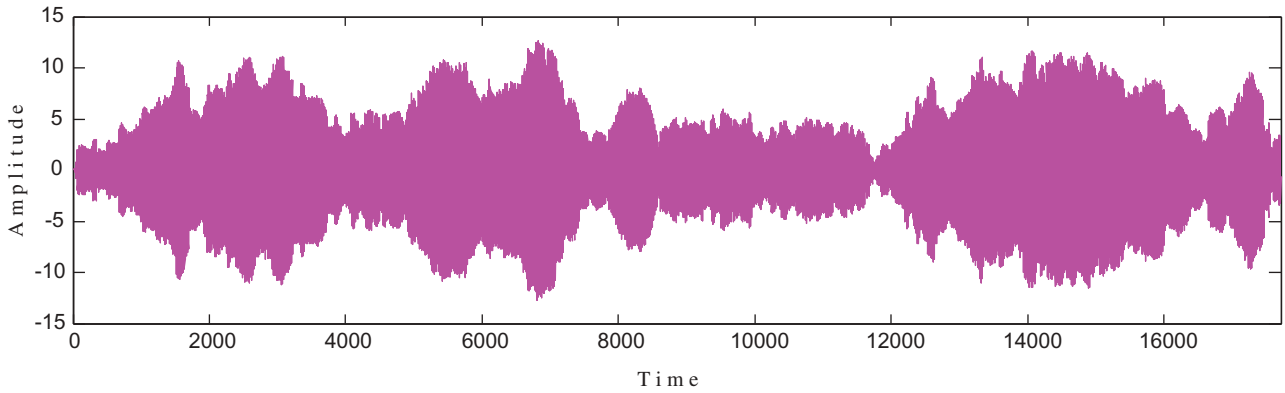


**Figure 9.** Recorded noisy signal at $d$ = 2.5 mm, $f$ = 0.05 mm/rev and $N$ = 700 rpm.

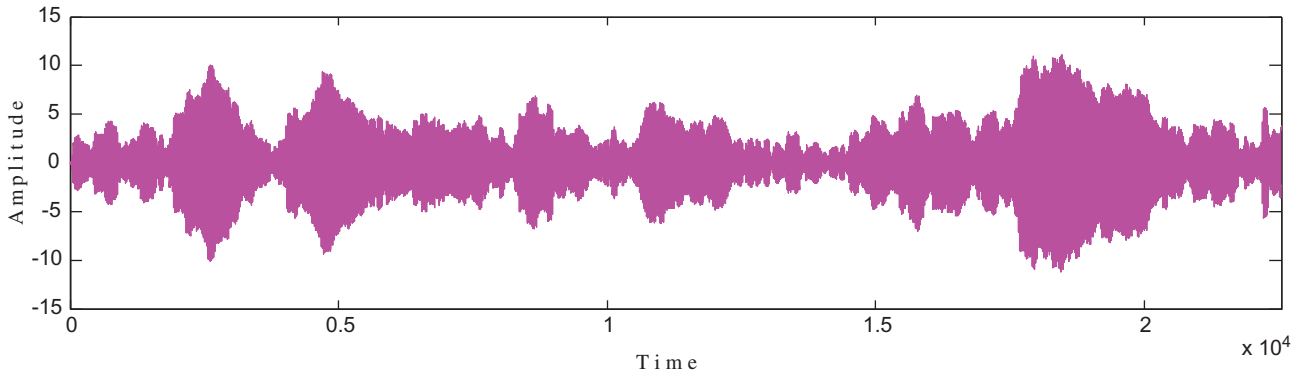


**Figure 10.** Recorded noisy signal at $d$ = 2.5 mm, $f$ = 0.05 mm/rev and $N$ = 1300 rpm.

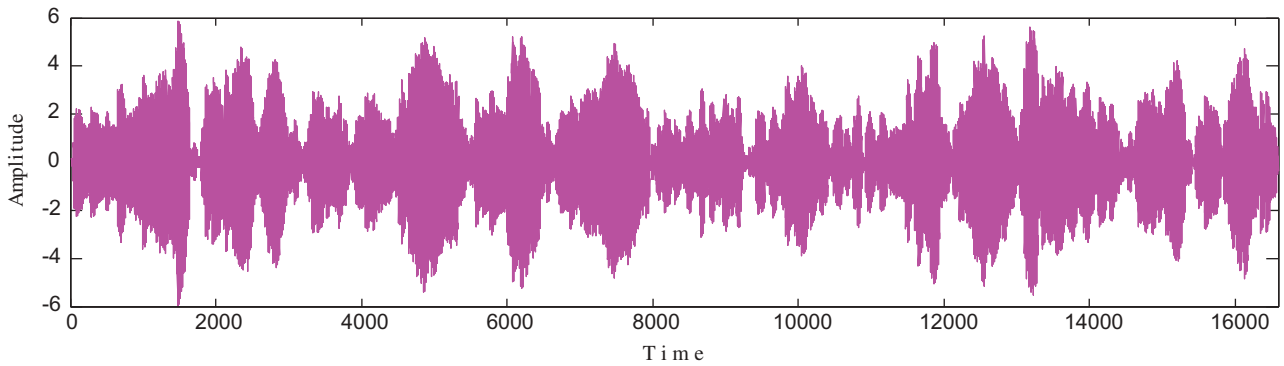


**Figure 11.** Recorded noisy signal at $d$ = 2.5 mm, $f$ = 0.25 mm/rev and $N$ = 700 rpm.

$$d_{(\text{coded})} = \frac{d - 1.5}{1},\ f_{(\text{coded})} = \frac{f - 0.15}{0.1},\ N_{(\text{coded})} \frac{N - 1000}{300} \tag{11}$$

CI: Chatter index.

### 7.2. Mathematical models of tool chatter

Chatter is an unavoidable phenomenon and sometimes it is very difficult to predict the exact nature of chatter. Hence, it is necessary to develop a suitable model which successfully yields proper relation between input (cutting parameters) and output (CI). In this study, RSM has been adopted to develop both quadratic and cubic models for CI in terms of cutting parameters ($d$, $f$ and $N$). As per estimated regression coefficients, the quadratic and cubic models for CI have been developed and are given by Equations (12) and (13), respectively:

$$\begin{aligned} CI_{\text{quadratic}} = {} & 0.85 + 0.77 \times d - 0.47 \times f + 0.041 \times N \\ & - 0.45 \times d \times f - 0.54 \times d \times N + 0.36 \times f \times N \\ & - 0.035 \times d \times d + 0.25 \times f \times f + 1.08 \times N \times N \end{aligned} \tag{12}$$

$$\begin{aligned} CI_{\text{cubic}} = {} & 0.81 + 0.68 \times d - 0.37 \times f - 0.061 \times N \\ & - 0.45 \times d \times f - 0.54 \times d \times N + 0.36 \times f \times N \\ & - 0.049 \times d \times d + 0.28 \times f \times f + 1.11 \times N \times N \\ & + 0.036 \times d \times f \times N - 0.13 \times d \times d \times f \\ & + 0.13 \times d \times d \times N + 0.13 \times d \times f \times f \end{aligned} \tag{13}$$

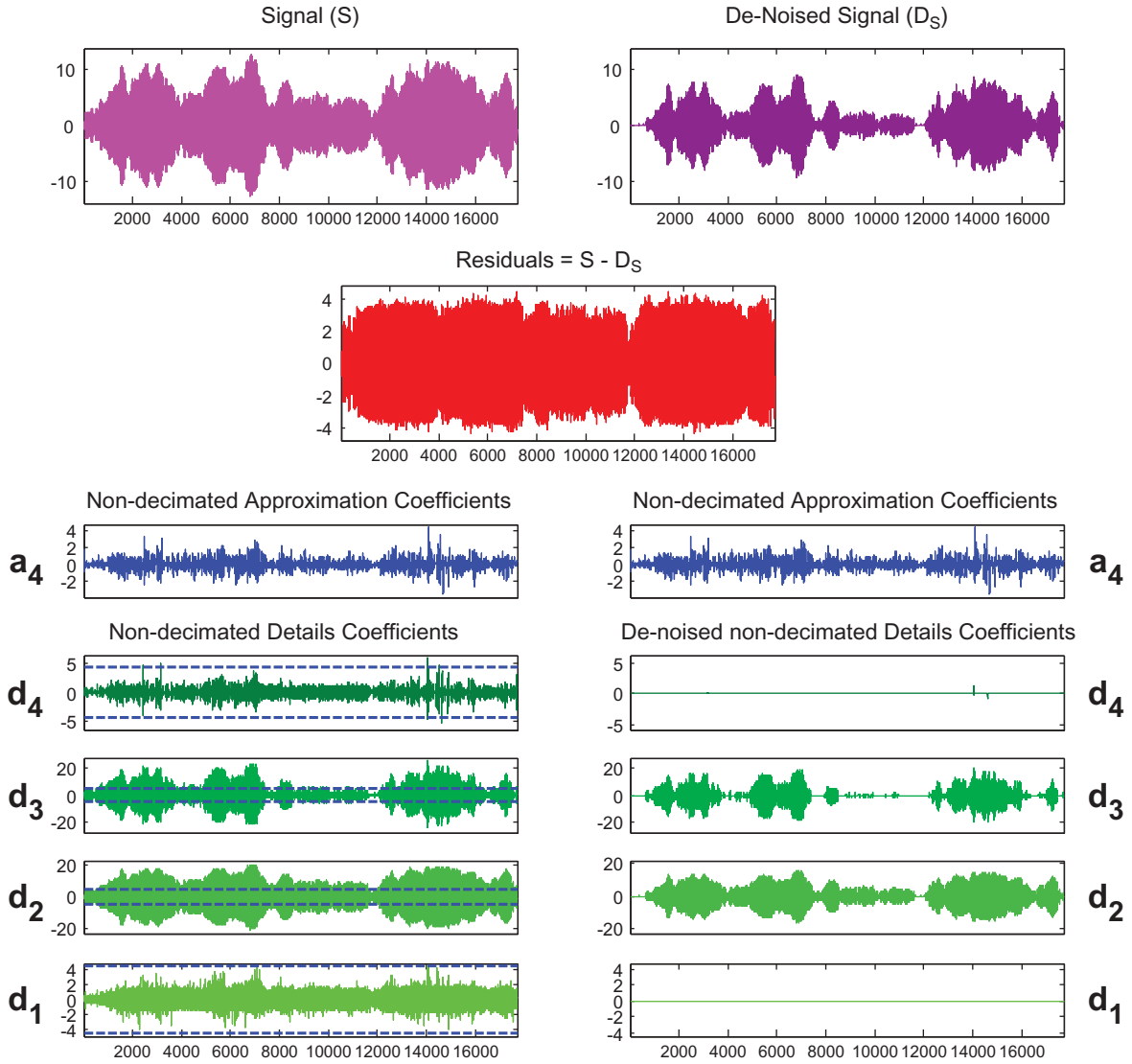


**Figure 12.** De-noising of signal at $d$ = 2.5 mm, $f$ = 0.05 mm/rev and $N$ = 700 rpm.

Moreover, after developing the RSM models (quadratic and cubic), it is required to find out among these two the most suitable model for predicting dependency of chatter severity on cutting parameters. Table 4 shows the experimental and RSM models-based predicted values of CI.

CI: Chatter index.

### 7.3. Selection of RSM model

In order to find out the suitability of developed models, error between experimental and predicted values has been calculated. For this, the following equation has been used and is given by

$$e_{ai} = \left(\frac{V_E - V_P}{V_E}\right) \times 100\ \% \tag{14}$$

where $e_{ai}$ represents average individual error, $V_E$ and $V_P$ are the experimental and predicted values, respectively.

Table 5 represents the individual and average percentage error for both quadratic and cubic models. From Table 5, it is evident that the proposed cubic model is best suited for giving the relation between input and output variables and thus it is quite appropriate for chatter prediction. Here, the average percentage error is found to be 7.7% for quadratic model and 0.5% for cubic model.

Above discussion concludes that the higher order term in mathematical model gives better results. A good agreement between experimental and predicted values for quadratic model and cubic model is shown in Figure 15. Moreover, chatter severity prediction with the help of regression and 3D plots based on cubic model has been presented in Figures 16–27 and discussed in next article.

### 7.4. Chatter prediction using regression and 3D plots (for cubic model)

From the discussion in previous section, it is quite clear that the cubic model is best suited for chatter prediction. In order to check the statistical error in considering range

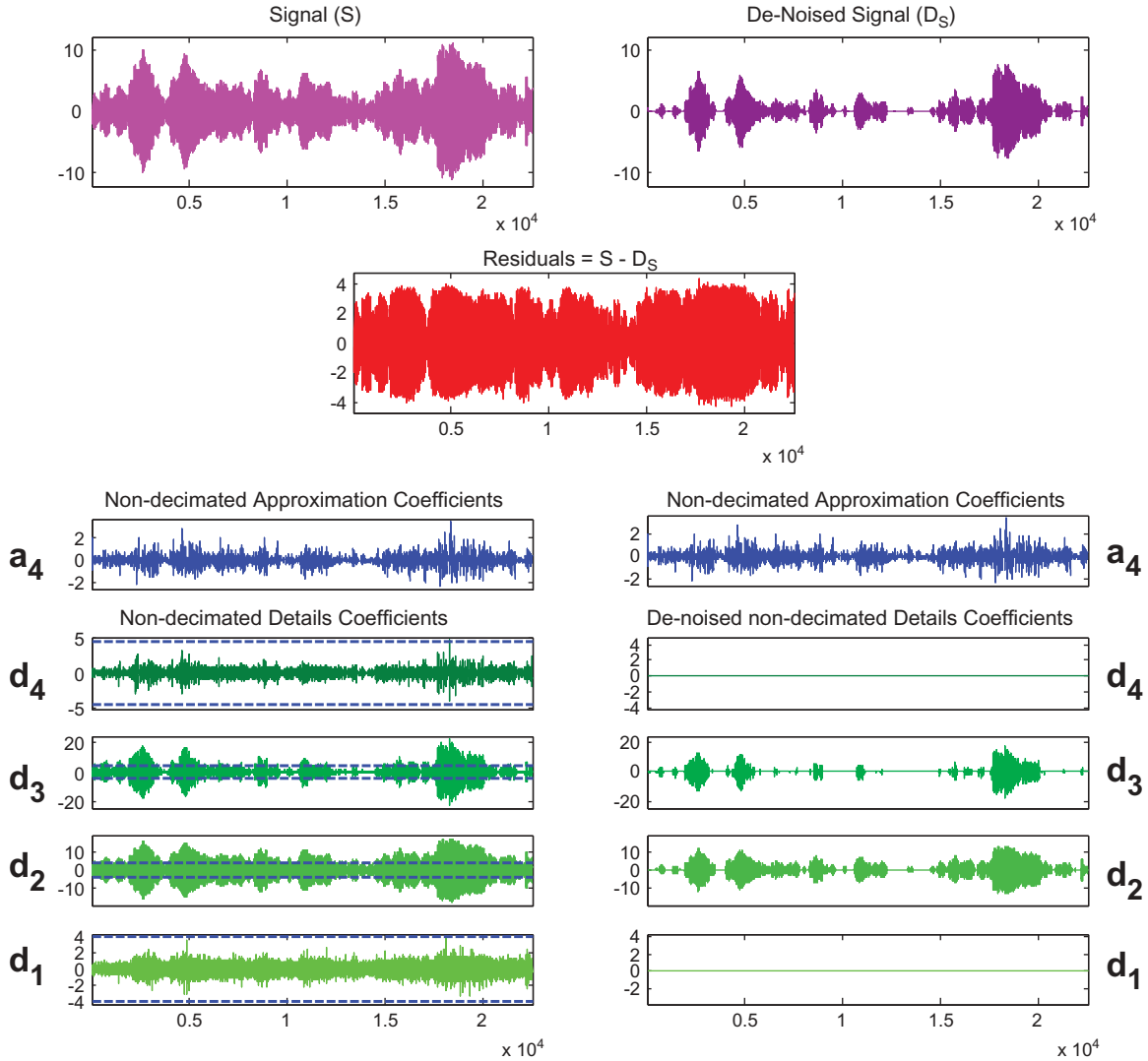


**Figure 13.** De-noising of signal at $d$ = 2.5 mm, $f$ = 0.05 mm/rev and $N$ = 1300 rpm.

and values of machining parameters for developing the cubic model, standard error of design has been plotted as shown in Figures 16–18. The shape of this plot depends on the design points (cutting parameter) and the polynomial being fit. If the design and model selected is statistically correct, then the curve is a flat error profile centred in the middle of the design space. In case of RSM, this plot should appear as either a circle or a square of uniform precision. Figure 16 shows that the standard error of design has been found to be uniform (circle and square) and is thus favourable.

In order to check the statistical significance of the developed cubic model for CI, residual plots have been drawn. A normal plot of residual for CI is shown in Figure 19. Residual is defined as the difference between measured and predicted values. Figure 19 helps to give information for error and assumption made in the present study. Here, data are spread roughly along the straight line which indicates that the data are normally and independently distributed and assumptions are valid.

Furthermore, the regression plot between residuals and run number has been shown in Figure 20. This plot is used to find out the unequal error variances and detect non-linearity of regression model. Figure 20 shows that the maximum variation is in the range of −15 to 15 and does not reveal any obvious pattern. It also shows that all the residuals bounce randomly around zero line and thus indicate the error independency and assumptions that the linear relationship is fair.

Moreover, Figure 21 shows the plot of predicted versus actual results. Normal distribution of error is tested with the help of this plot. Here, actual and predicted values fall on a straight line and thus indicate the normal distribution of error.

Effect of interaction of cutting parameters with each other affects the chatter index and this is plotted as interaction plot as shown in Figures 22–24. Figure 22 shows that with the increase in both depth of cut and feed rate, chatter increases. Moreover, slope of depth of cut line is high comparatively and thus it is the most influencing parameter.

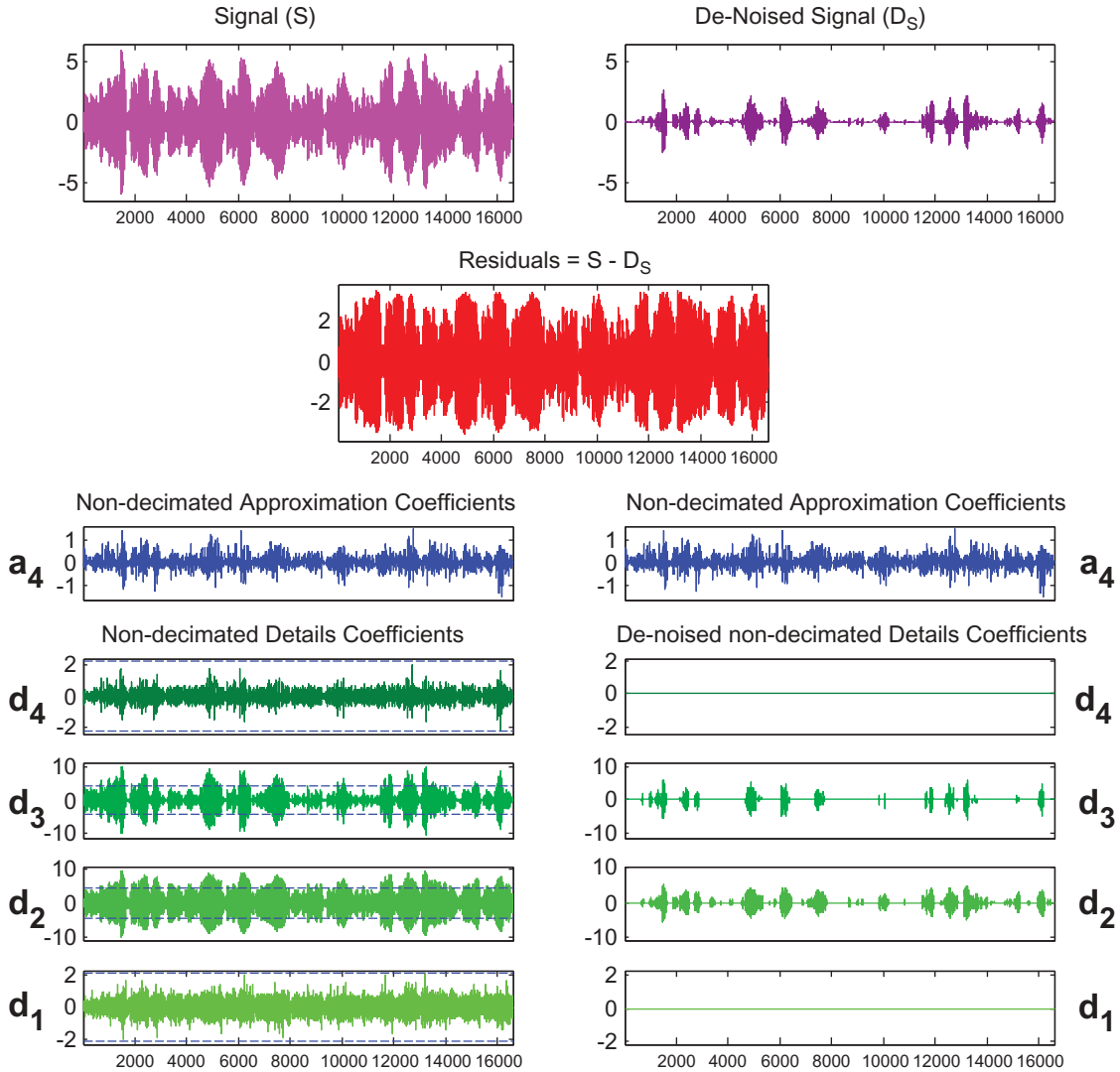


**Figure 14.** De-noising of signal at $d$ = 2.5 mm, $f$ = 0.25 mm/rev and $N$ = 700 rpm.

**Table 3.** Chatter index at different cutting conditions.

| Sr. no. | Depth of cut ($d$) mm | Feed rate ($f$) mm/rev | Spindle speed ($N$) rpm | CI |
|---|---|---|---|---|
| 1 | 0 | 0 | 0 | 0.804 |
| 2 | 0 | 0 | 0 | 0.803 |
| 3 | 0 | 0 | 0 | 0.805 |
| 4 | 1 | 0 | 0 | 1.442 |
| 5 | 0 | −1 | 0 | 1.46 |
| 6 | 1 | −1 | −1 | 4.781 |
| 7 | 0 | 0 | 0 | 0.804 |
| 8 | −1 | −1 | −1 | 1.103 |
| 9 | −1 | 1 | 1 | 2.228 |
| 10 | 0 | 1 | 0 | 0.717 |
| 11 | 0 | 0 | −1 | 1.986 |
| 12 | 1 | −1 | 1 | 3.042 |
| 13 | −1 | 1 | −1 | 0.367 |
| 14 | −1 | −1 | 1 | 1.665 |
| 15 | 0 | 0 | 0 | 0.804 |
| 16 | 1 | 1 | −1 | 2.081 |
| 17 | 0 | 0 | 0 | 0.803 |
| 18 | 0 | 0 | 1 | 1.863 |
| 19 | −1 | 0 | 0 | 0.081 |
| 20 | 1 | 1 | 1 | 1.931 |

**Table 4.** Experimental and modelled predicted values.

| Sr. no. | ($d$) | ($f$) | ($N$) | Experimental values for CI | Predicted values (quadratic) for CI | Predicted values (cubic) for CI |
|---|---|---|---|---|---|---|
| 1 | 0 | 0 | 0 | 0.804 | 0.85 | 0.81 |
| 2 | 0 | 0 | 0 | 0.803 | 0.85 | 0.81 |
| 3 | 0 | 0 | 0 | 0.805 | 0.85 | 0.81 |
| 4 | 1 | 0 | 0 | 1.442 | 1.585 | 1.441 |
| 5 | 0 | −1 | 0 | 1.46 | 1.57 | 1.46 |
| 6 | 1 | −1 | −1 | 4.781 | 4.694 | 4.778 |
| 7 | 0 | 0 | 0 | 0.804 | 0.85 | 0.81 |
| 8 | −1 | −1 | −1 | 1.103 | 1.174 | 1.106 |
| 9 | −1 | 1 | 1 | 2.228 | 2.296 | 2.224 |
| 10 | 0 | 1 | 0 | 0.717 | 0.63 | 0.72 |
| 11 | 0 | 0 | −1 | 1.986 | 1.889 | 1.981 |
| 12 | 1 | −1 | 1 | 3.042 | 2.976 | 3.044 |
| 13 | −1 | 1 | −1 | 0.367 | 0.414 | 0.358 |
| 14 | −1 | −1 | 1 | 1.665 | 1.616 | 1.676 |
| 15 | 0 | 0 | 0 | 0.804 | 0.85 | 0.81 |
| 16 | 1 | 1 | −1 | 2.081 | 2.134 | 2.086 |
| 17 | 0 | 0 | 0 | 0.803 | 0.85 | 0.81 |
| 18 | 0 | 0 | 1 | 1.863 | 1.971 | 1.859 |
| 19 | −1 | 0 | 0 | 0.081 | 0.045 | 0.081 |
| 20 | 1 | 1 | 1 | 1.931 | 1.856 | 1.936 |

Moreover, Figure 23 shows that chatter is fairly constant with increasing spindle speed while with the increase in depth of cut chatter increases.

Figure 24 shows that the slope of variation line of feed rate is almost constant and it has less effect on chatter. Here, slope of variation line of spindle speed

**Table 5.** Error evaluations of proposed RSM models.

| Sr. no. | (*d*) | (*f*) | (*N*) | Experimental CI | Predicted (quadratic) CI | % Error (quadratic) | Predicted (cubic) CI | % Error (cubic) |
|---|---|---|---|---|---|---|---|---|
| 1 | 0 | 0 | 0 | 0.804 | 0.85 | −5.7 | 0.81 | −0.7 |
| 2 | 0 | 0 | 0 | 0.803 | 0.85 | −5.9 | 0.81 | −0.9 |
| 3 | 0 | 0 | 0 | 0.805 | 0.85 | −5.6 | 0.81 | −0.6 |
| 4 | 1 | 0 | 0 | 1.442 | 1.585 | −9.9 | 1.441 | 0.1 |
| 5 | 0 | −1 | 0 | 1.46 | 1.57 | −7.5 | 1.46 | 0.0 |
| 6 | 1 | −1 | −1 | 4.781 | 4.694 | 1.8 | 4.778 | 0.1 |
| 7 | 0 | 0 | 0 | 0.804 | 0.85 | −5.7 | 0.81 | −0.7 |
| 8 | −1 | −1 | −1 | 1.103 | 1.174 | −6.4 | 1.106 | −0.3 |
| 9 | −1 | 1 | 1 | 2.228 | 2.296 | −3.1 | 2.224 | 0.2 |
| 10 | 0 | 1 | 0 | 0.717 | 0.63 | 12.1 | 0.72 | −0.4 |
| 11 | 0 | 0 | −1 | 1.986 | 1.889 | 4.9 | 1.981 | 0.3 |
| 12 | 1 | −1 | 1 | 3.042 | 2.976 | 2.2 | 3.044 | −0.1 |
| 13 | −1 | 1 | −1 | 0.367 | 0.414 | −12.8 | 0.358 | 2.5 |
| 14 | −1 | −1 | 1 | 1.665 | 1.616 | 2.9 | 1.676 | −0.7 |
| 15 | 0 | 0 | 0 | 0.804 | 0.85 | −5.7 | 0.81 | −0.7 |
| 16 | 1 | 1 | −1 | 2.081 | 2.134 | −2.5 | 2.086 | −0.2 |
| 17 | 0 | 0 | 0 | 0.803 | 0.85 | −5.9 | 0.81 | −0.9 |
| 18 | 0 | 0 | 1 | 1.863 | 1.971 | −5.8 | 1.859 | 0.2 |
| 19 | −1 | 0 | 0 | 0.081 | 0.045 | 44.4 | 0.081 | 0.0 |
| 20 | 1 | 1 | 1 | 1.931 | 1.856 | 3.9 | 1.936 | −0.3 |
| Average % error | | | | | | 7.7 | | 0.5 |

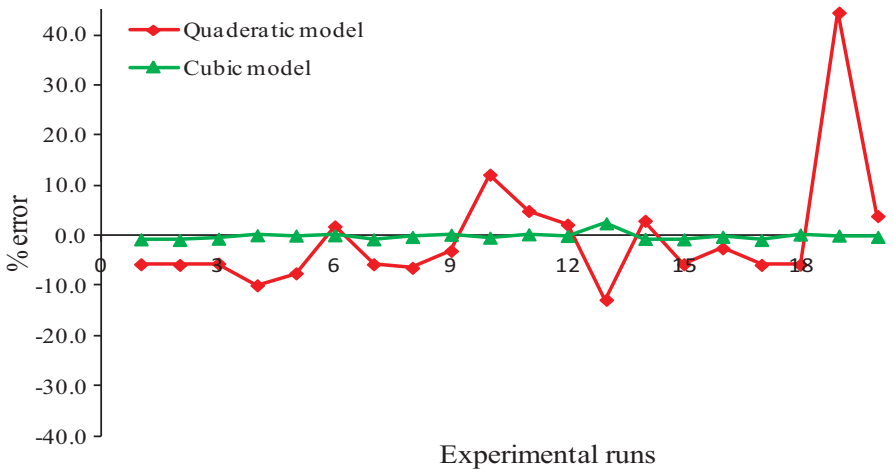


**Figure 15.** Comparison of % error of RSM models.

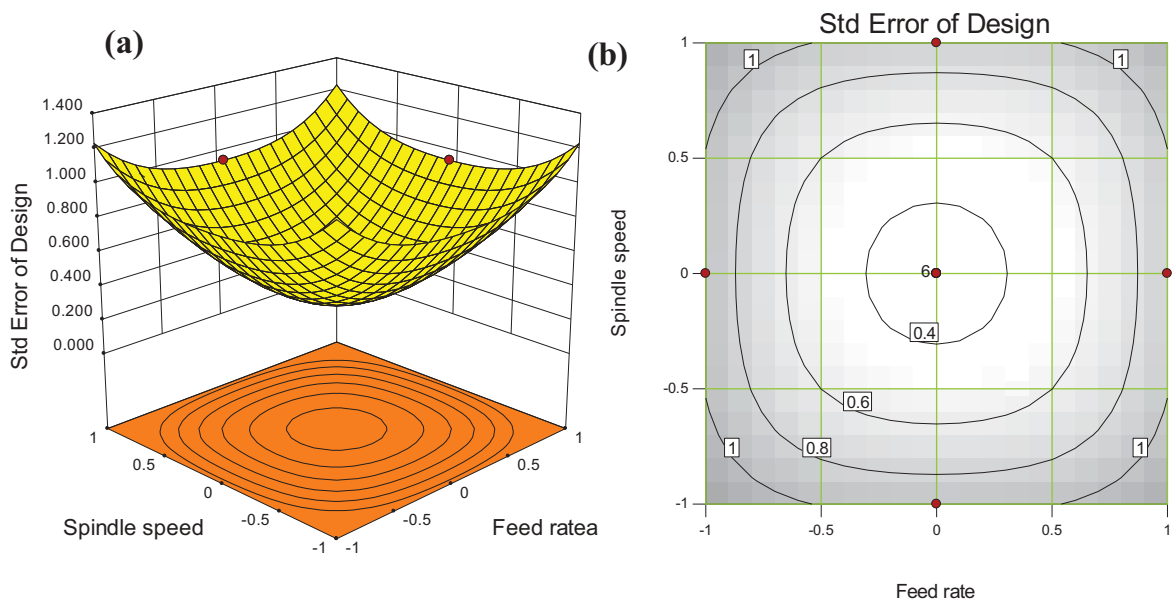


**Figure 16.** Variation of standard error w.r.t. spindle speed and feed rate (a) surface plot and (b) contour plot.

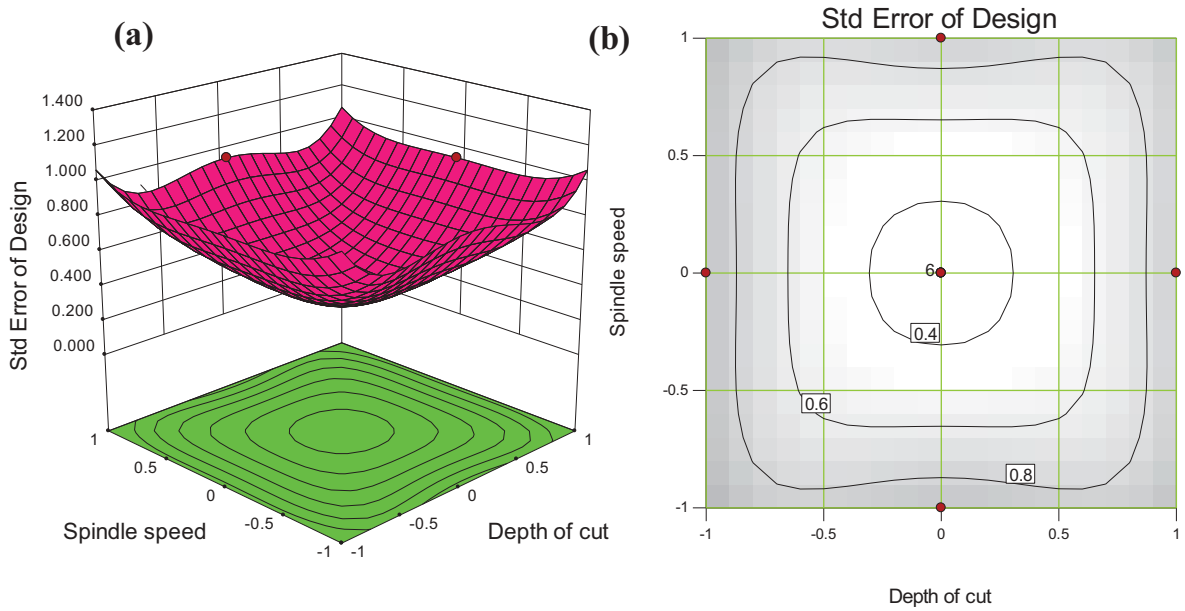


**Figure 17.** Variation of standard error w.r.t. spindle speed and depth of cut (a) surface plot and (b) contour plot.

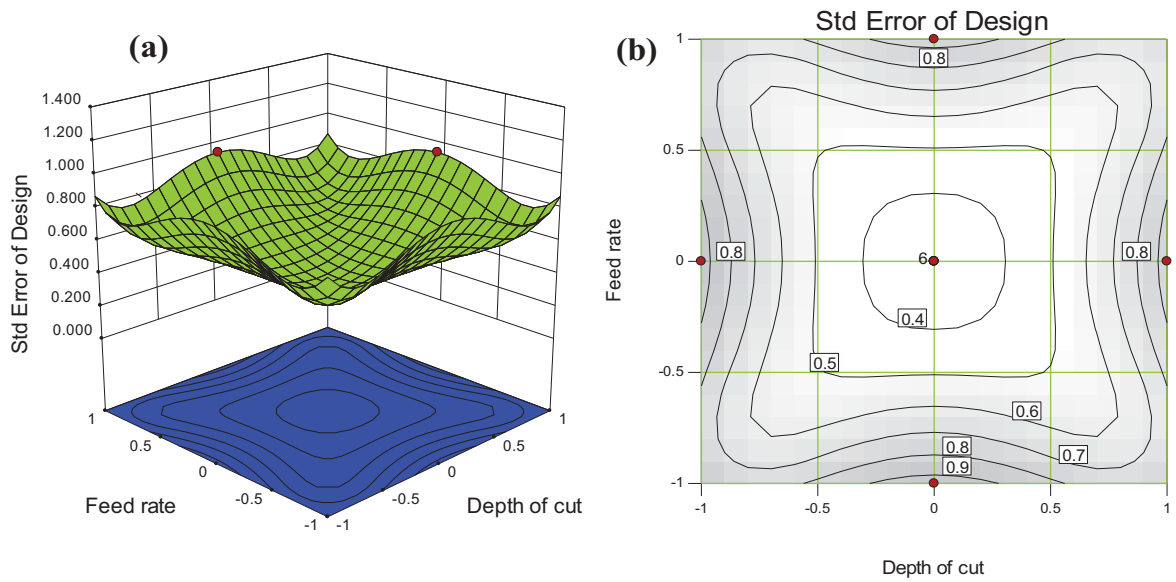


**Figure 18.** Variation of standard error w.r.t. feed rate and depth of cut (a) surface plot and (b) contour plot.

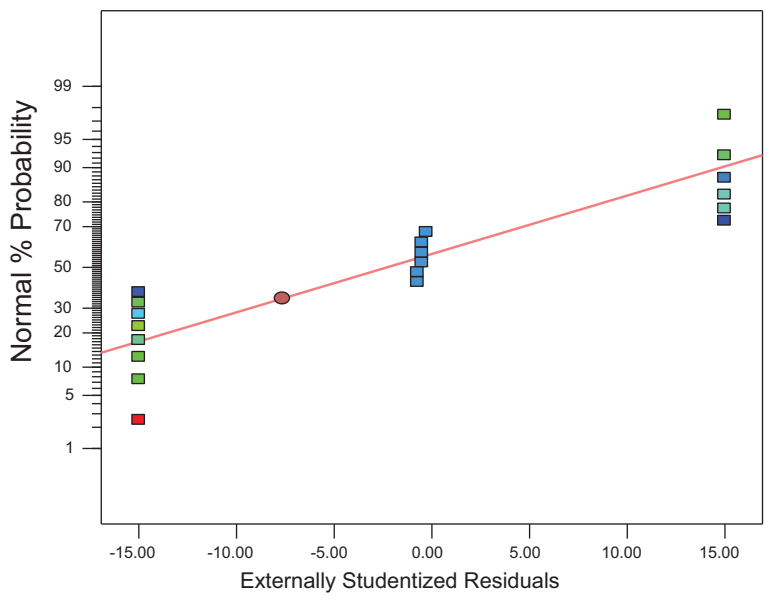


**Figure 19.** Normal probability plot for residuals.

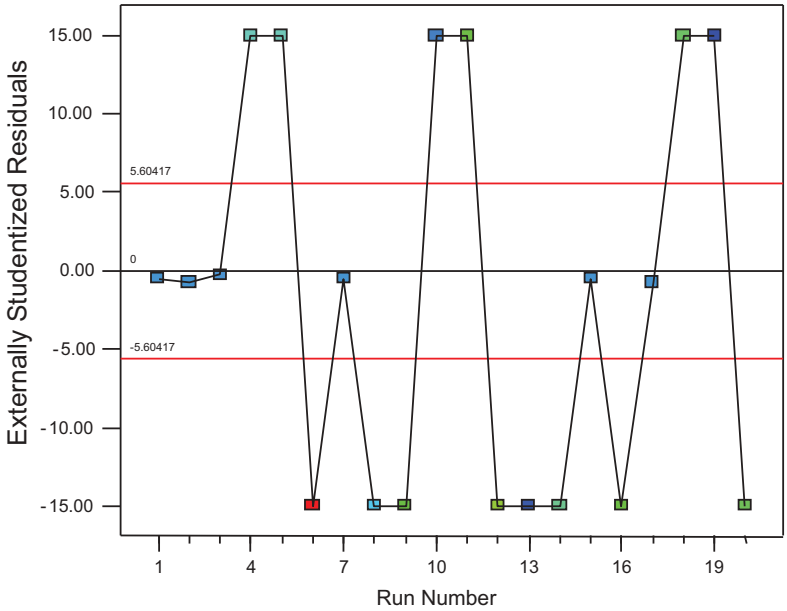


**Figure 20.** Plot of residuals versus run number.

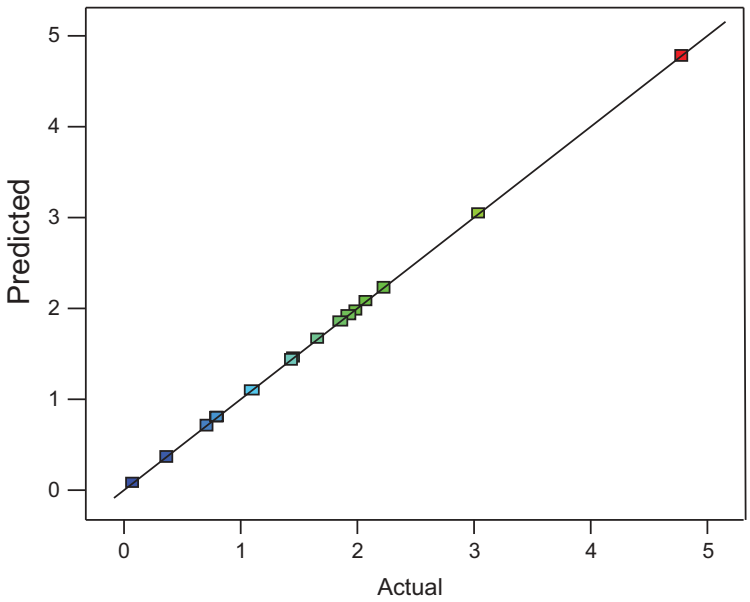


**Figure 21.** Plot of predicted versus actual results.

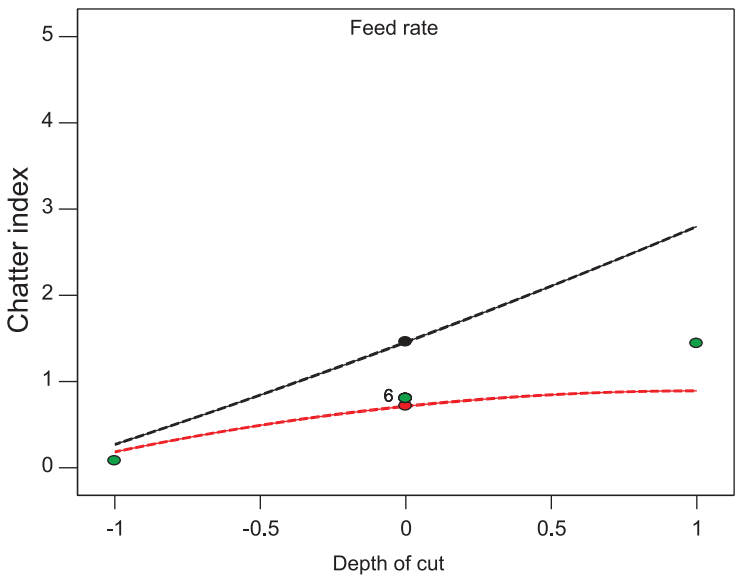


**Figure 22.** Interaction effect of depth of cut (black line) and feed rate (red line) on CI.

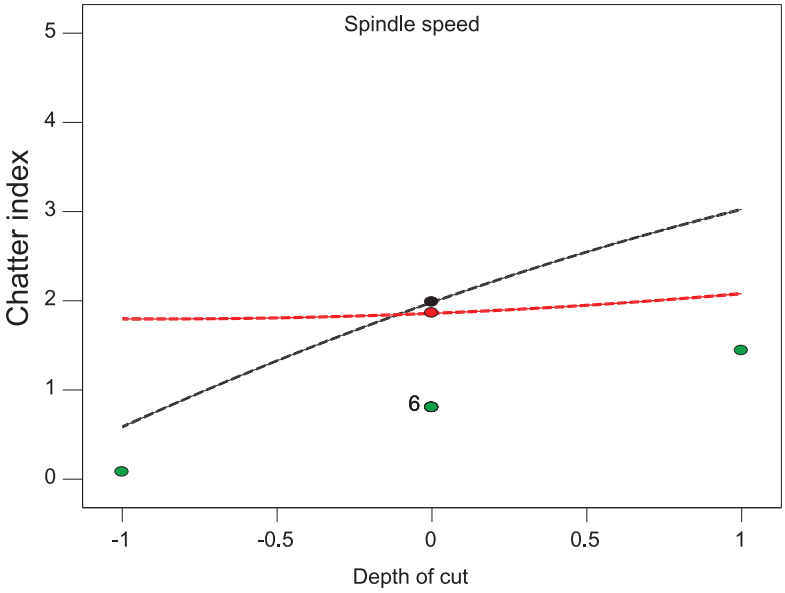


**Figure 23.** Interaction effect of depth of cut (black line) and speed (red line) on CI.

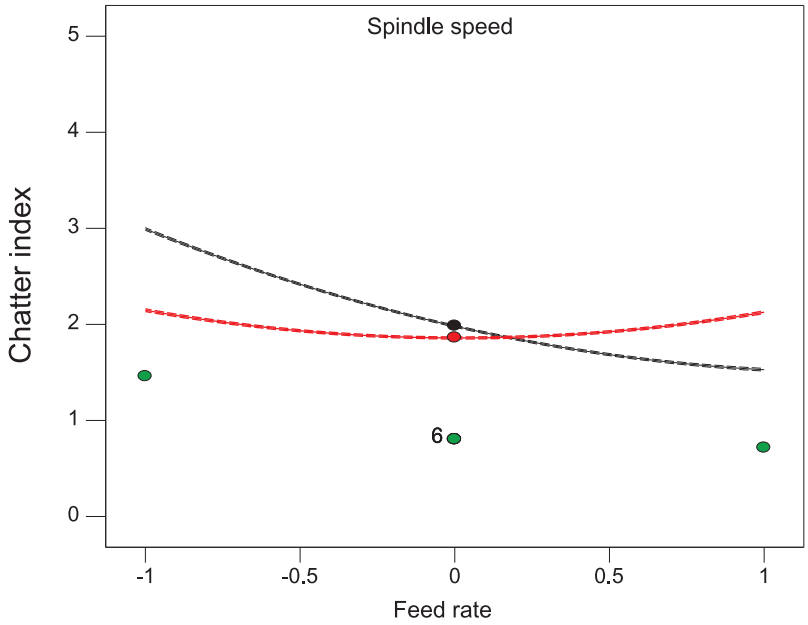


**Figure 24.** Interaction effect of feed rate (red line) and spindle speed (black line) on CI.

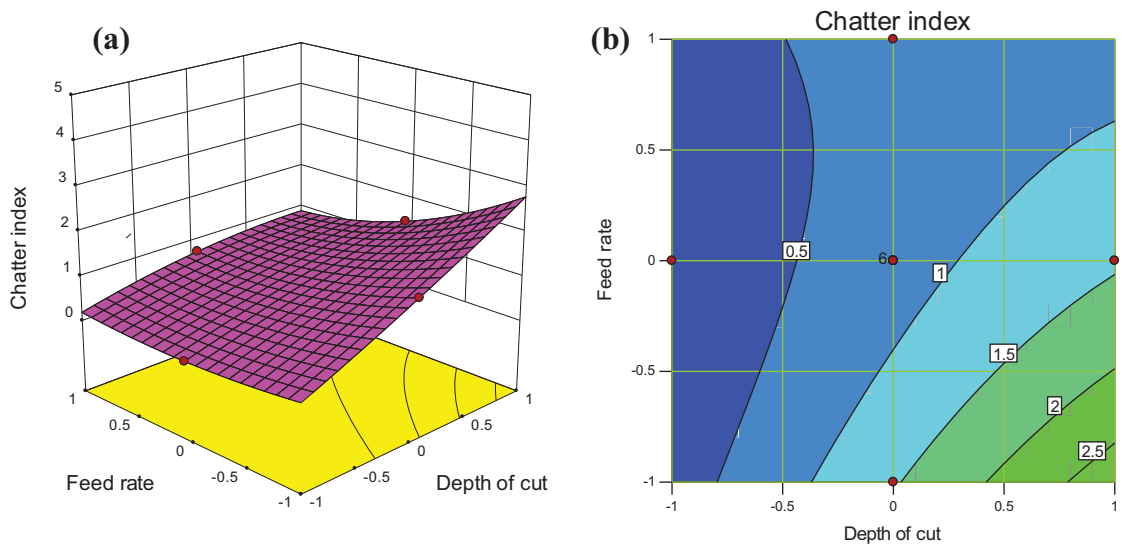


**Figure 25.** Combined effects of feed rate and depth of cut on chatter index (a) response surface plot and (b) contour plot.

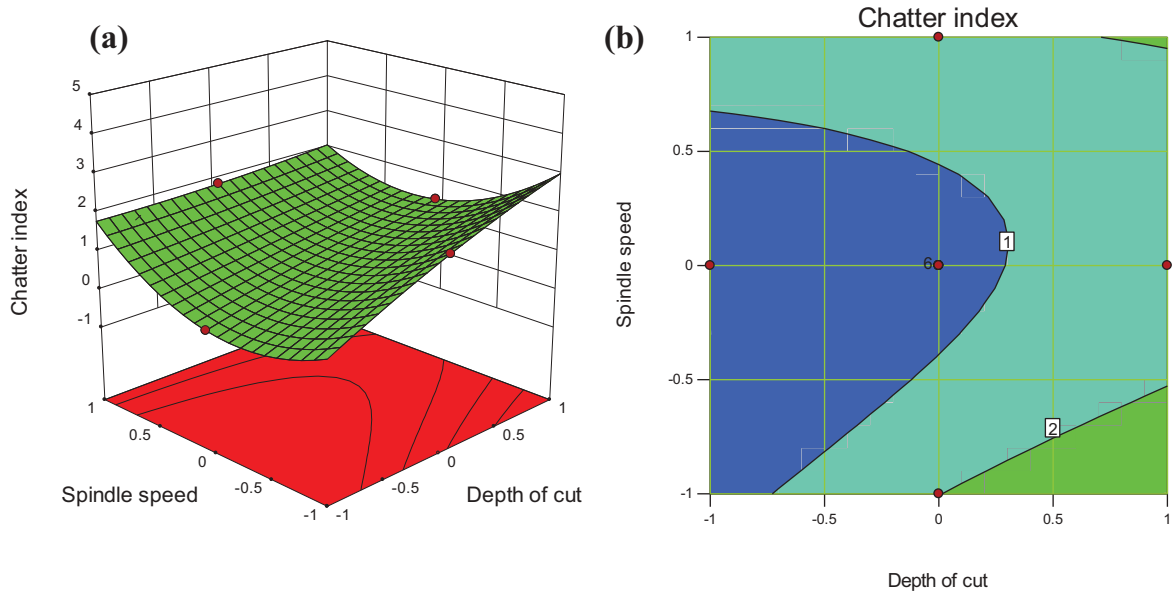


**Figure 26.** Combined effects of spindle speed and depth of cut on chatter index (a) response surface plot and (b) contour plot.

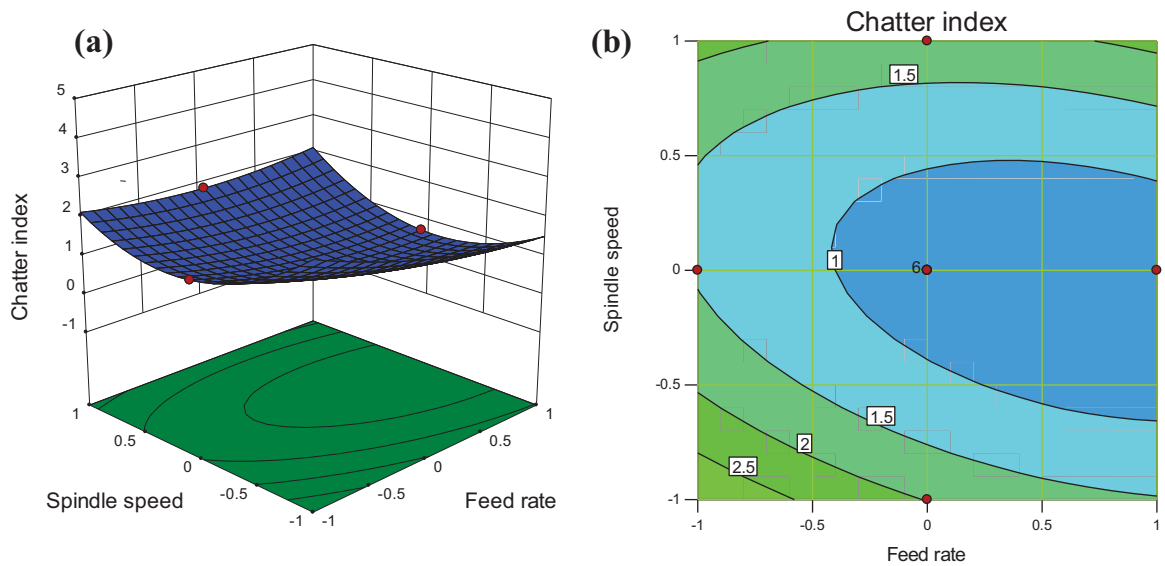


**Figure 27.** Combined effects of spindle speed and feed rate on chatter index (a) response surface plot and (b) contour plot.

**Table 6.** Cubic model base ANOVA for chatter index (CI).

| Source | Sum of squares | df | Mean square | *F*-value | *p*-Value (Prob > *F*) |
|---|---|---|---|---|---|
| Model | 21.56 | 13 | 1.66 | 76,446.86 | <0.0001 |
| *d* | 0.93 | 1 | 0.93 | 42,686.17 | <0.0001 |
| *f* | 0.28 | 1 | 0.28 | 12,721.80 | <0.0001 |
| *N* | 7.565E − 003 | 1 | 7.565E − 003 | 348.64 | <0.0001 |
| $d \times f$ | 1.65 | 1 | 1.65 | 76,249.38 | <0.0001 |
| $d \times N$ | 2.32 | 1 | 2.32 | 1.071E + 005 | <0.0001 |
| $f \times N$ | 1.04 | 1 | 1.04 | 48,051.32 | <0.0001 |
| $d^2$ | 6.481E − 003 | 1 | 6.481E − 003 | 298.70 | <0.0001 |
| $f^2$ | 0.21 | 1 | 0.21 | 9827.48 | <0.0001 |
| $N^2$ | 3.42 | 1 | 3.42 | 1.574E + 005 | <0.0001 |
| $d \times f \times N$ | 0.011 | 1 | 0.011 | 484.51 | <0.0001 |
| $d^2 \times f$ | 0.026 | 1 | 0.026 | 1180.05 | <0.0001 |
| $d^2 \times N$ | 0.026 | 1 | 0.026 | 1212.93 | <0.0001 |
| $d \times f^2$ | 0.026 | 1 | 0.026 | 1217.66 | <0.0001 |
| Residual | 1.302E − 004 | 6 | 2.170E − 005 | | <0.0001 |
| Lack of fit | 1.273E − 004 | 1 | 1.273E − 004 | 224.73 | <0.0001 |
| Pure error | 2.833E − 006 | 5 | 5.667E − 007 | | |
| Cor total | 21.56 | 19 | | | |

*R*-squared: 99.43%, Adj. *R*-squared: 98.20%

**Table 7.** Validation checks of proposed models.

| Sr. no. | (*d*) | (*f*) | (*N*) | Experimental CI | Predicted CI (quadratic) | % Error (quadratic) | Predicted CI (cubic) | % Error (cubic) |
|---|---|---|---|---|---|---|---|---|
| 1 | −1 | 0 | −1 | 0.585 | 0.544 | 7.0 | 0.582 | 0.5 |
| 2 | −1 | 0 | 1 | 1.790 | 1.706 | 4.7 | 1.8 | −0.6 |
| 3 | 0 | −1 | 1 | 2.155 | 2.331 | −8.2 | 2.149 | 0.3 |
| 4 | 0 | 1 | −1 | 1.525 | 1.309 | 14.2 | 1.531 | −0.4 |
| 5 | 1 | −1 | 0 | 2.815 | 2.755 | 2.1 | 2.801 | 0.5 |
| 6 | 1 | 0 | −1 | 3.000 | 3.164 | −5.5 | 3.022 | −0.7 |
| 7 | −1 | −1 | 0 | 0.283 | 0.315 | −11.3 | 0.281 | 0.7 |
| Total average % error | | | | | | 7.6 | | 0.5 |

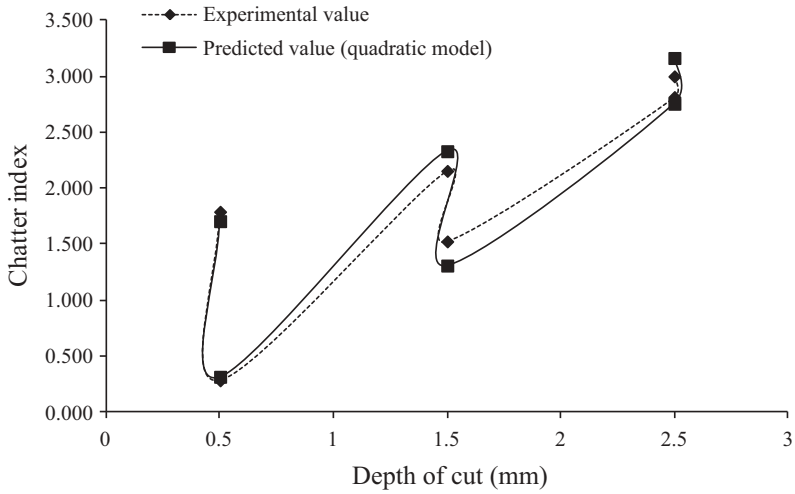


**Figure 28.** Predicted versus experimental chatter index for depth of cut (quadratic model).

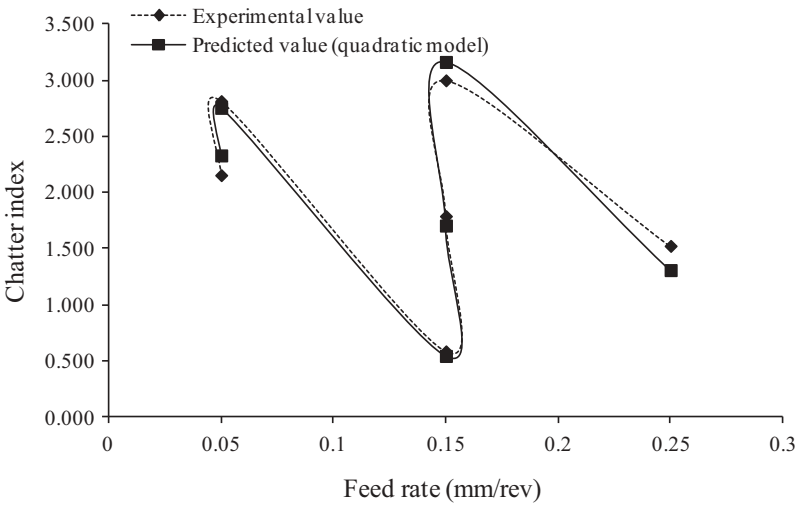


**Figure 29.** Predicted versus experimental chatter index for feed rate (quadratic model).

is negative which shows that with the increase in spindle speed, chatter decreases.

From the above discussion, it has been inferred that at same value of feed rate and spindle speed, chatter can be maximum or minimum depending on the depth of cut. This indicates that the dependency of CI on the cutting parameters is not monotonous. From the above discussion, it is also evident that the depth of cut is the most influencing parameter. The reason is, with the increase in depth of cut keeping other parameters constant, the associated radial force increases prominently as compared to the other cutting forces. This increase in radial force results in increased waviness and unevenness along the surface of the workpiece. This waviness leads to further time delay between the two corresponding turning passes along the job surface. So, ultimately, increase in depth of cut results in pronounced tool chatter as compared to the rest of the cutting parameters. Furthermore, to represent the exact non-monotonous behaviour of CI, response surface and contour plots have been drawn as shown in Figures 25–27. Figure 25 shows the effect of feed rate and depth of cut on CI while keeping spindle speed in central value. Figure 25 shows that the optimal value of chatter can be achieved by setting feed rate in the range of −1 to 1 mm/rev (coded value) and depth of cut from −1 to −0.80 mm (coded value).

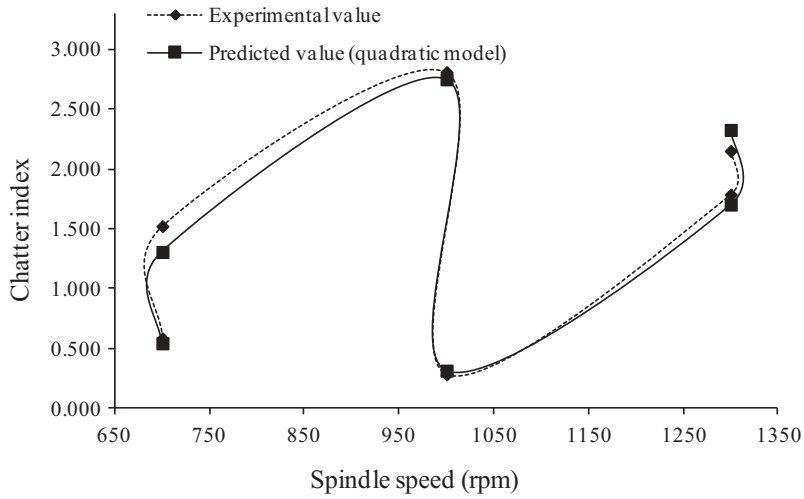


**Figure 30.** Predicted versus experimental chatter index for spindle speed (quadratic model).

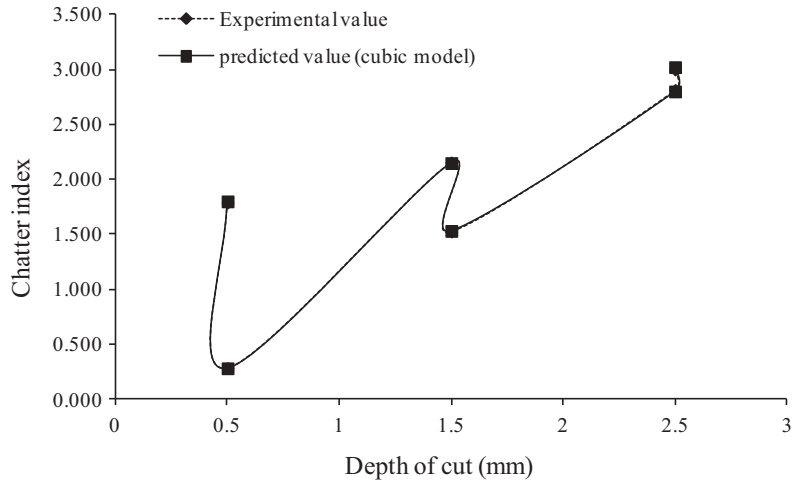


**Figure 31.** Predicted versus experimental chatter index for depth of cut (cubic model).

Moreover, Figure 26 shows the effect of spindle speed and depth of cut on chatter when keeping the value of feed rate in middle range. From Figure 26, it is evident that the less chatter is obtained by setting the spindle speed from −0.1 to 0 rpm (coded) and depth of cut from −1 to 0.80 mm (coded). With the aforesaid combination, the value of CI less than 1 (i.e. 0.8–0.9) can be found and it will be the safe cutting zone.

Figure 27 shows the effect of spindle speed and feed rate on chatter when keeping the value of depth of cut in middle range. In Figure 27, the contour plot shows that the less chatter (0.7–0.9) is achieved by setting the spindle speed from −0.80 to 0.50 rpm (coded) and feed rate from 0 to 1 mm/rev (coded).

From the above discussion, it can be seen that the dependence of chatter on cutting parameters is non-monotonous.

### 7.5. ANOVA for CI (for cubic model)

ANOVA has been done to check the adequacy of the developed RSM models of responses by using three tests named as significance of regression model, significance of model coefficients and test of lack of fit. Table 6 shows the ANOVA results for CI. Analysis has been done at the confidence interval of 99%. In statistical analysis, the value of $R$-sq. indicates the accuracy of model while $R$-sq. (adj.) value shows the compatibility of model with experimental data. In Table 6, the value of $R$-sq. is 99.43% and $R$-sq. (adj.) is 98.20% while model $p$-value is found to be less than 0.0001 and it proves that the model is statistically significant. Furthermore, values of $p$-value (Prob > $F$) less than 0.01 indicate the significant model terms and hence all terms are the significant. Table 6 indicates that the 'lack-of-fit $p$-value' is less than 0.0001 and it also conveys that the lack of fit is significant.

## 8. Validation of developed RSM models

From the above discussion, it is clear that the proposed cubic model could be successfully used to predict CI in turning process. Moreover, in order to check the validity of the developed models, more experiments have been

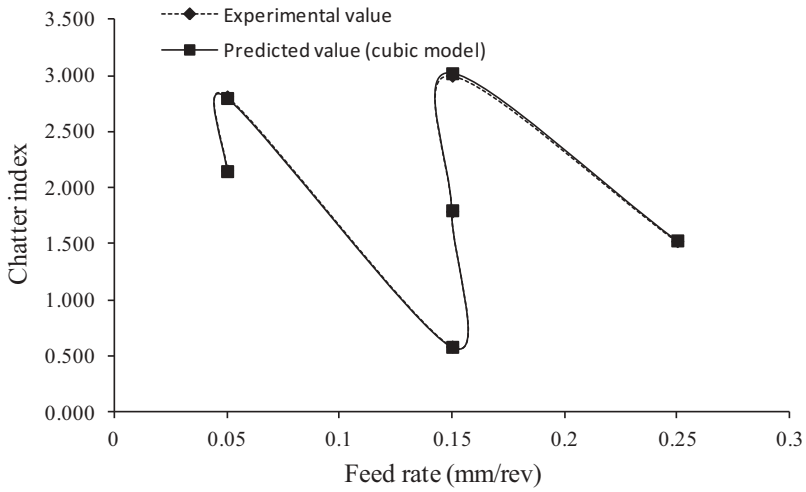


**Figure 32.** Predicted versus experimental chatter index for feed rate (cubic model).

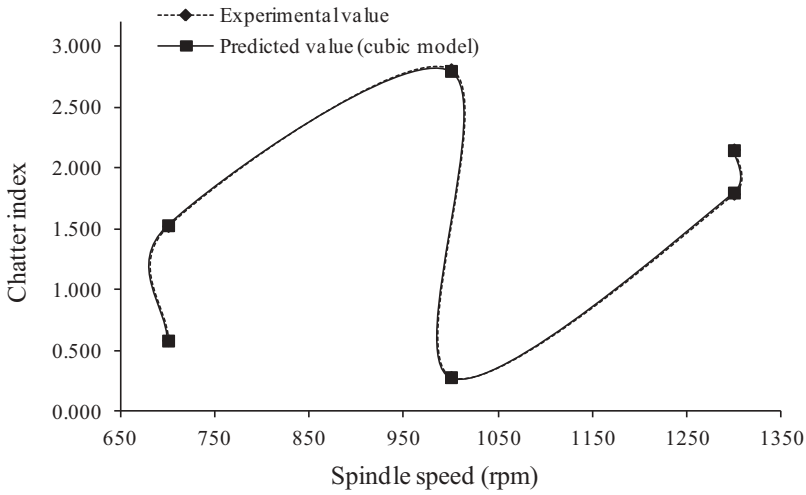


**Figure 33.** Predicted versus experimental chatter index for spindle speed (cubic model).

performed as shown in Table 7. For this purpose, Equation (14) has been utilised. A good agreement between experimental and predicted values validates the developed RSM models and is shown in Figures 28–30 for quadratic and Figures 31–33 for cubic model.

## 9. Optimisation of cutting parameters

In the present work, response optimiser has been considered to obtain the optimised values of cutting parameters: depth of cut ($d$), feed rate ($f$) and spindle speed ($N$). It is one of the most important tools in RSM used to get the optimum values of cutting parameters. The aim of this work is to minimise CI. Optimum results for responses have been predicted with the help of optimiser plots as shown in Figure 34. Figure 34 revealed that the minimum CI (0.118) has been obtained at optimum settings of the cutting parameters of $d$ = 0.50 mm, $f$ = 0.760 mm/rev and $N$ = 956 rpm.

## 10. Conclusion

In the present work, a series of experiments has been performed to acquire the raw chatter signals in turning process. After de-noising these raw signals using WT, CI has been evaluated. Further, quadratic and cubic models considering RSM have been developed for chatter. ANOVA is done to check the adequacy of the developed. Moreover, after validation, the following conclusions have been drawn:

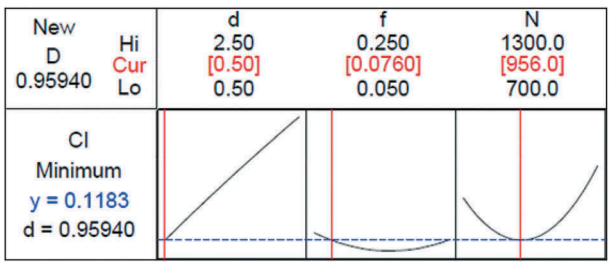


**Figure 34.** RSM optimisation plot for chatter index (CI).

(1) Raw chatter signals are supremely pre-processed by WT.
(2) RSM-based cubic mathematical model shows well correlation between cutting parameter and chatter severity as compared to quadratic model.
(3) ANOVA test revealed that the cubic model is better for chatter prediction.
(4) The regression plots and developed model reflect that depth of cut is the most influencing parameter in comparison to feed rate and spindle speed.
(5) Minimum CI (0.118) has been obtained at optimum settings of the cutting parameters of $d$ = 0.50 mm, $f$ = 0.760 mm/rev and $N$ = 956 rpm.
(6) Dependence of chatter on cutting parameters is non-monotonous in nature.
(7) During validation test, average prediction error has been found to be 7.6% for quadratic and 0.5% for cubic model.
(8) It is pertinent to mention that the results obtained in this paper are valid under fixed cutting condition and machining environment. Further variation in any cutting and machining condition may change the output results.

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## Disclosure statement

No potential conflict of interest was reported by the authors.

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