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Predictive Modelling and Optimization of Chip Strain for Early Warning of Tool Breakage in Dry Drilling Using Response Surface Methodology and Artificial Neural Network

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Abstract

Tool breakage remains a critical limitation in dry drilling because unexpected failure can compromise machining accuracy, damage the workpiece, increase production downtime, and raise tooling costs. However, fracture is preceded by deformation of the generated chip, suggesting that chip strain may provide a measurable precursor to impending tool failure. This study investigates chip strain at the onset of tool breakage as an early-warning response variable and develops predictive and optimization models relating its behaviour to controllable drilling parameters. Feed rate, cutting speed, and depth of cut were investigated during dry drilling of mild steel using a central composite experimental design. Response Surface Methodology (RSM) was employed to quantify the individual, interaction, and quadratic effects of the drilling parameters, while an Artificial Neural Network (ANN) was developed as an alternative data-driven predictive model. The quadratic RSM model exhibited strong predictive performance, with $R^2 = 0.9627$, Adjusted $R^2 = 0.9291$, and an adequate precision of 19.198. Analysis of variance showed that the interaction between cutting speed and depth of cut exerted the strongest influence on chip strain ($F = 31.77$), ($p < 0.0002$), followed by the quadratic effects of depth of cut ($F = 51.45$), ($p < 0.0001$), and cutting speed ($F = 31.77$), ($p = 0.0002$). Numerical optimization identified a minimum predicted chip strain of 0.0253804 at a feed rate of 0.30 mm/rev, cutting speed of 146.22 m/min, and depth of cut of 0.50 mm, with an overall desirability of 93.1%. The ANN yielded $R^2 = 76.56\%$, with the experimental-to-predicted relationship expressed as (Experimental = $0.004602 + 0.8654$ ANN). The superior performance of the RSM model further demonstrates the importance of interaction and quadratic effects in describing strain development under the investigated drilling conditions.

Keywords: Chip Strain; Tool Breakage; Dry Drilling; Fracture Prediction; Response Surface Methodology; Artificial Neural Network; Machining Optimization.

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1. INTRODUCTION

Cutting force is the most commonly monitored parameter in machining research, though it is a late

indicator of tool breakage (Kasiviswanathan *et al.*, 2024; Souflas *et al.*, 2025; Wojciechowski *et al.*, 2025). Force

rises gradually as the tool wears, but the final fracture event is often preceded by milliseconds of sudden strain localization in the chip (Qin *et al.*, 2026). Strain which is a measure of plastic deformation before fracture, captures the material's approach to its failure limit (Yazdanparast & Rafiee, 2024). In dry drilling, where temperatures are high as a result of the absence of cooling, the chip material undergoes severe plastic shear. When this shear strain exceeds the material's ductility limit, the chip fractures (Nelson & Nair, 2025). The drill survives if the chip fracture is clean and timely but if the chip fails to fracture or fractures in an uncontrolled manner, torque spikes, and the drill breaks. Thus, chip strain at fracture is not only a post mortem characteristic, but a predictor for imminent tool failure. As a function of variables that the operator can control, including feed rate, cutting speed and depth of cut, strain can be modelled to determine combinations that keep the strain below the fracture limit and reduce the risk of breakage. The multi-region model for the properties of the chip material has been developed by Zhu *et al.* (2026) based on the kinematic and geometric analysis to characterize the distribution and evolution of strain and strain rate along the cutting-edge direction and cutting-speed direction. A three-dimensional finite element model (FEM) was then developed to help validate the theoretical model and gain greater understanding of the effect of strain and strain rate on chip formation. Unlike lubricated drilling, where coolant reduces temperature and strain rate, dry drilling allows the full thermal-strain coupling to manifest (Sen *et al.*, 2025; Tian *et al.*, 2026). As cutting speed increases, the strain rate at the chip root increases proportionally (Man *et al.*, 2026). However, higher speeds also generate more heat, which thermally softens the material and reduce the stress required for continued deformation which creates a non-monotonic relationship: strain may initially increase with speed, then decrease as thermal softening dominates (Han *et al.*, 2024). Depth of cut introduces a different mechanism because the larger depths the more the volume of material being sheared, increasing both force and strain. However, the chip also becomes thicker, which may promote earlier fracture due to bending stresses. The interaction between speed and depth is therefore critically important for strain prediction. Recent studies have increasingly applied statistical and machine-learning techniques to predict machining responses, optimize drilling parameters, and monitor tool-condition changes during drilling operations. Onyiruika *et al.* (2024) employed Response Surface Methodology (RSM) and Artificial Neural Network (ANN) based on a central composite design to predict and optimize cutting forces during dry drilling. RSM demonstrated a stronger predictive capability than the ANN for the investigated drilling conditions. Corne *et al.* (2017) employed ANN using spindle-power data to predict tool wear and breakage during Inconel 625 drilling. The result emphasised that the model produced generally low prediction errors. Munaro *et al.* (2024) extracted features from acoustic emission, vibration, spindle power, and

spindle torque and compared ANN and Random Forest (RF) models for tool-wear monitoring during AISI 9840 drilling. The RF model showed stronger and more reliable classification performance than ANN. However, the study concentrated on tool wear rather than directly predicting chip strain or using strain evolution as an early indicator of tool breakage. Domínguez-Monferrer *et al.* (2022) developed a machine-learning framework based on spindle-power features and machining-history variables for monitoring tool-wear evolution during automated CFRP drilling. The study showed strong predictive capability, with RF outperforming the other investigated learning approaches. The authors concluded that the most important predictors from their study were accumulated cutting time and maximum spindle power. Han *et al.* (2025) applied RSM in conjunction with genetic algorithm (GA) to optimize chip evacuation behaviour in gun drilling of oxygen-free copper. The investigation identified feed rate as a particularly influential parameter and established machining conditions associated with favourable chip formation and evacuation.

The reviewed studies demonstrate substantial applications of RSM, ANN, and machine-learning techniques to drilling forces, chip behaviour, and tool-condition monitoring. However, existing research predominantly treats cutting force, torque, chip morphology, chip evacuation, and tool wear as separate responses, with limited attention to chip strain as a direct indicator of impending tool failure. Therefore, the present study addresses this gap by integrating RSM and ANN to predict and optimize chip strain during dry drilling and establish its potential for early warning of tool breakage. The main contributions of the present study are summarized as follows:

- (i) Establishment of chip strain as an early-warning indicator of tool breakage in dry drilling, extending the assessment of tool-condition behaviour beyond conventional machining responses.
- (ii) Development of an integrated RSM and ANN modelling framework for characterizing and predicting chip-strain behaviour under varying drilling conditions.
- (iii) Identification and optimization of critical drilling conditions governing chip strain, providing a basis for parameter selection and early detection of conditions associated with tool-breakage risk.

The remainder of this paper is organized as follows. Section 2 presents the materials and methods adopted for the investigation; which details the workpiece and tooling specifications, experimental design, formulation of the RSM model, development and training of the ANN, and the numerical optimization procedure. Section 3 presents and discusses the results, including model selection and adequacy assessment, ANOVA-based evaluation of parameter effects, goodness-of-fit and residual diagnostics, response-surface interactions, numerical optimization of chip strain, and ANN-based prediction. The present study is summarized in Section 4, which consolidates the principal findings on chip-strain

behaviour, the predictive performance of the developed models, the optimized drilling conditions, implications of chip strain as an early-warning indicator for tool breakage, scientific contributions, and suggested future research.

2. MATERIALS AND METHODS

2.1 Workpiece Material and Tooling

Mild steel plates with the dimensions of 100 mm × 400 mm × 50 mm were used as the workpiece material due to their industrial relevance, availability, and cost-effectiveness. Mild steel has moderate to medium-high machineability but is susceptible to built-up edges when dry. This is a suitable test material for the study of tool breakage susceptibility. A DT drilling machine was used for the whole experiments. The drill bits used were high-speed steel (HSS) twist drills, which are the most popular type of drill used in small and medium manufacturing

companies and are very susceptible to thermal and mechanical overload.

2.2 Experimental Design Using Central Composite Design

The choice of Central Composite Design (CCD) was made over simpler factorial designs because it efficiently captures curvature in the response surface and allows estimation of quadratic effects with a relatively small number of experimental runs. CCD is a combination of factorial design ($2^3 = 8$ runs), six axial points ($\alpha = \pm 1.682$), and six center points, yielding a total of 20 experimental runs. The center points were replicated to provide a pure error estimate and to assess model lack-of-fit. The three input parameters, their coded and actual ranges are shown in Table 1 as seen below.

Table 1: Input Parameters and Experimental Ranges

Parameter	Symbol	Units	Low (1.682)	Low (1)	Centre (0)	High (+1)	High (+1.682)
Feed rate	A	mm/rev	0.03	0.10	0.20	0.30	0.37
Cutting speed	B	m/min	106.36	120.00	140.00	160.00	173.64
Depth of cut	C	mm	0.33	0.50	0.75	1.00	1.17

2.3 Response Surface Methodology

RSM was implemented using Design-Expert software (version 7.01) to quantify the functional dependence of chip strain at breakage on three controllable machining parameters: feed rate, cutting speed, and depth of cut. The RSM approach offers distinct advantages over conventional one-factor-at-a-time experimentation by simultaneously capturing interaction effects and nonlinear curvature with a reduced number of experimental trials (Cheng & Tang, 2026), thus enabling efficient process optimization. Experimental data were fitted to a second-order quadratic polynomial, whose general mathematical form is given in Eqn. 1 (Chen & Chen, 2025; Vo-Thanh et al., 2026), where Y denotes the predicted strain on chip at time of breakage, X_j represents the coded input variables (feed rate, cutting speed, depth of cut), β_0 is the intercept (response at center point), β_j is the linear coefficients (main effects), β_{ij} denotes the interaction coefficients (synergistic or antagonistic effects between pairs of variables), β_{jj} represents the quadratic coefficients (curvature effects), and ε is the random experimental error.

$$Y = \beta_0 + \sum_{j=1}^3 \beta_j X_j + \sum_{j=1}^3 \beta_{jj} X_j^2 + \sum_{i < j}^3 \beta_{ij} X_i X_j + \varepsilon \dots 1$$

The choice of quadratic model was made over linear,

interactive (2FI), and cubic alternatives based on sequential model sum of squares tests, which evaluate whether adding higher-order terms significantly improves model fit. The 2nd order polynomial was chosen because it showed a significant improvement over the 2FI model ($p < 0.0001$). The cubic model was aliased (insufficient unique runs to estimate all coefficients), and it provided the highest predicted R^2 with the lowest PRESS (predicted residual error sum of squares). Model adequacy was rigorously assessed using multiple statistical criteria such as sequential F-tests. This was basically to determine the significance of added terms, lack-of-fit tests to verify that the model does not systematically miss underlying patterns (non-significant lack-of-fit is desired), Coefficient of determination (R^2) has been widely employed in previous studies (Adeleke et al., 2025; Okwu et al., 2024; Oyejide et al., 2025) to measure the proportion of variance explained by a model. It is used in the present study to evaluate the developed RSM models. Also adjusted R^2 to penalize unnecessary terms, predicted R^2 to evaluate predictive capability on new data (calculated from PRESS) and adequate precision (signal-to-noise ratio), where a value greater than 4 indicates the model can navigate the design space reliably. Additionally, variance inflation factors (VIF) were monitored to discover multicollinearity among terms (VIF

≈ 1.0 is ideal). Residual diagnostics including normal probability plots of studentized residuals and Cook's distance were employed to authenticate assumptions of normality, constant variance, and the absence of influential outliers. The final 2nd order polynomial model was expressed in terms of actual (uncoded) factors to facilitate direct industrial implementation without transformation.

2.4 Artificial Neural Network

A multilayer feedforward neural network was developed using MATLAB in order to complement the parametric RSM approach. ANNs serve as universal function approximators which can capture complex, nonlinear relationships without assuming a specific functional form (Chakraborty & Chakraborty, 2024; Dornheim et al., 2023); which serves as an advantage when modeling dry drilling, where thermal softening, strain hardening, and chip clogging introduce significant nonlinearities. The network design consists of three layers and these include: an input layer with 3 neurons (feed rate, cutting speed, depth of cut), a single hidden layer with 10 neurons employing a log-sigmoid transfer function (logsig) to introduce nonlinearity, and an output layer with 1 neuron (strain on chip) using a linear transfer function (purelin). The hidden layer size was optimized via trial-and-error (4 to 20 neurons), with 10 neurons selected as the minimum configuration that minimized validation error without overfitting. All experimental data were normalized to the [0,1] range using min–max scaling to prevent variables with larger magnitudes (e.g., cutting speed) from dominating weight updates. Normalization parameters were derived exclusively from the training set to avoid data leakage. The Levenberg–Marquardt backpropagation algorithm was employed for training because of its superior convergence speed and numerical stability for function approximation problems compared to standard gradient descent. Training terminated automatically when the validation error failed to decrease for six consecutive epochs (early stopping), a strategy that prevents overfitting by halting training before the network begins to memorize noise. The overall network performance was evaluated based on the completely unseen testing set using the coefficient of determination (R^2) and mean squared error (MSE). RSM gave a

transparent 2nd order polynomial equation, ANN offered a flexible, high-capacity alternative better suited for detecting subtle nonlinearities, though with the trade-off of reduced interpretability.

2.5 Numerical Optimization and Validation

Numerical optimization was performed using the desirability function approach, which combines multiple response targets into a single composite score (0 to 1). The objective was to minimize strain on chip. All three input parameters were constrained within their experimental ranges. The solution with the highest desirability was selected as optimal. Confirmation experiments were not part of the original thesis scope but are recommended for future work.

3. RESULTS

3.1 Modelling and Optimization using RSM

RSM is a systematic method for understanding the relationship between several input variables and one or more response variables. This method is now used in many industries where optimization of the process is critical and there is a need for statistical modelling. In the present study, the optimization objective was to minimize chip strain at breakage. The final optimization solution entailed identifying optimal values of the input variables—feed rate, cutting speed, and depth of cut—that yield minimal strain. To generate experimental data for optimization, the following procedure was adopted. For this purpose, a statistical design of experiments (DOE) was carried out using the CCD method which is commonly used in optimization studies by researchers using RSM. Based on this DOE, an experimental design matrix was created with 6 centre points, 6 axial points, and 8 factorial points for a total of 20 experimental runs. Design-Expert 7.01 software was employed to implement both the experimental design and subsequent process optimization. The sequential model sum of squares was calculated for the measured chip strain to check the adequacy of the quadratic model for the experimental data, as shown in Table 2.

Table 2: Sequential Model Sum of Square for Strain on Chip

Source	Sum of Squares	df	Mean Square	F Value	p-value	Prob > F
Mean vs Total	1.3×10^{-2}	1	1.3×10^{-2}			
Linear vs Mean	8.543×10^{-5}	3	2.848×10^{-5}	0.84		0.4908
2FI vs Linear	3.088×10^{-4}	3	1.029×10^{-4}	5.76		0.0099
Quadratic vs 2FI	2.091×10^{-4}	3	6.969×10^{-5}	29.81		< 0.0001
Cubic vs Quadratic	1.145×10^{-5}	4	2.861×10^{-6}	1.44		0.3283
Residual	1.193×10^{-5}	6	1.989×10^{-6}			
Total	1.4×10^{-2}	20	7.060×10^{-4}			

The sequential model sum of squares represents the amount of improvement in the model fit caused by adding each term sequentially. The highest-order model that statistically retained additional terms without aliasing was determined as the optimum polynomial order. As shown in Table 2, the cubic polynomial exhibited aliasing and was therefore excluded from further consideration. Both the quadratic and two-factor interaction (2FI) models were

recommended as adequate fits, supporting the adoption of a quadratic polynomial for this analysis. A lack-of-fit test was conducted on the response to test the ability of the quadratic model to explain the underlying variation in experimental results. Models displaying significant lack of fit are unsuitable for predictive purposes. Table 3 presents the lack of fit results of the computed chip strain.

Table 3: Lack of Fit Test for Measured Strain on Chip

Source	Sum of Squares	df	Mean Square	F Value	p-value	Prob > F
Linear	5.325×10^{-4}	11	4.841×10^{-5}	27.40	0.0009	
2FI	2.236×10^{-4}	8	2.795×10^{-5}	15.82	0.0037	
Quadratic	1.455×10^{-5}	5	2.909×10^{-6}	1.65	0.2987	
Cubic	3.101×10^{-6}	1	3.101×10^{-6}	1.76	0.2426	
Pure Error	8.833×10^{-6}	5	1.767×10^{-6}			

Table 3 shows that the quadratic polynomial had non-significant lack of fit and was recommended for model analysis, while the cubic polynomial had significant lack of fit and was aliased and therefore not recommended. A model standard error analysis was conducted to further

assess the appropriateness of RSM using the quadratic model for minimizing 'chip strain'. Table 4 shows computed standard errors that correspond to the selected response.

Table 4: Result of Computed Standard Errors

Term	StdErr**	VIF	R-Squared	0.5 Std. Dev.	1 Std. Dev.	2 Std. Dev.
A	0.27	1.00	0.0000	13.3 %	38.6 %	91.4 %
B	0.27	1.00	0.0000	13.3 %	38.6 %	91.4 %
C	0.27	1.00	0.0000	13.3 %	38.6 %	91.4 %
AB	0.35	1.00	0.0000	9.8 %	24.9 %	72.2 %
AC	0.35	1.00	0.0000	9.8 %	24.9 %	72.2 %
BC	0.35	1.00	0.0000	9.8 %	24.9 %	72.2 %
A ²	0.26	1.02	0.0179	40.4 %	92.7 %	99.9 %
B ²	0.26	1.02	0.0179	40.4 %	92.7 %	99.9 %
C ²	0.26	1.02	0.0179	40.4 %	92.7 %	99.9 %

As shown in Table 4, the model exhibited low standard errors: 0.27 for individual (linear) terms, 0.35 for combined (interaction) effects, and 0.26 for quadratic terms. The standard errors should be similar within each type of coefficient, and smaller values representing more precise estimates. The error values for all experiments were lower than the baseline value of the model i.e. 1.0 which indicates that RSM was appropriate for the optimization problem. As shown in Table 4, variance

inflation factors (VIF) were near one, indicating low levels of multicollinearity (VIF values above 10 are usually interpreted as evidence of poorly estimated coefficients, indicating severe collinearity). One-way analysis of variance (ANOVA) was used to assess the predictive capacity of the second-order polynomial model for minimizing chip strain and the results are presented in Table 5.

Table 5: ANOVA Table for Validating Model Significance Strain on Chip

Source	Sum of Squares	df	Mean Square	F Value	p-value	Prob > F
Model	6.034×10^{-4}	9	6.704×10^{-5}	28.68		< 0.0001
A-feed rate	4.295×10^{-6}	1	4.295×10^{-6}	1.84		0.2051
B-cutting speed	4.202×10^{-5}	1	4.202×10^{-5}	17.97		0.0017
C-depth of cut	3.912×10^{-5}	1	3.912×10^{-5}	16.73		0.0022
AB	4.753×10^{-5}	1	4.753×10^{-5}	20.33		0.0011
AC	2.531×10^{-6}	1	2.531×10^{-6}	1.08		0.3226
BC	2.588×10^{-4}	1	2.588×10^{-4}	110.69		< 0.0001
A ²	1.441×10^{-5}	1	1.441×10^{-5}	6.16		0.0324
B ²	7.428×10^{-5}	1	7.428×10^{-5}	31.77		0.0002
C ²	1.203×10^{-4}	1	1.203×10^{-4}	51.45		< 0.0001
Residual	2.338×10^{-5}	10	2.338×10^{-6}			
Lack of Fit	1.455×10^{-5}	5	2.909×10^{-6}	1.65		0.2987
Pure Error	8.833×10^{-6}	5	1.767×10^{-6}			
Cor Total	6.267×10^{-4}	19				

Analysis of variance (ANOVA) was performed to assess overall model significance and to quantify the relative contributions of individual variables, interaction effects, and second-order polynomial terms to each

response. To further validate the adequacy of the quadratic model in minimizing chip strain, goodness-of-fit statistics were computed and are presented in Table 6.

Table 6: GOF for Validating Model Significance Strain on Chip

Std. Dev.	1.529×10^{-3}	R²	0.9627
Mean	0.026	Adj. R-Squared	0.9291
C.V. %	5.89	Pred. R-Squared	0.8036
PRESS	1.231×10^{-4}	Adeq. Precision	19.198

The difference between the predicted R² value of 0.8036 and the adjusted R² value of 0.9291 was within the commonly accepted limit of 0.20 as indicated in Table 6, therefore the predicted value showed reasonable agreement with the adjusted value. The signal-to-noise ratio, determined by sufficient precision, returned the result of 5.89, which is higher than the lowest value

recommended (4.0), indicating that the model had an adequate signal for navigating the design space. Accordingly, the developed quadratic model was considered suitable for minimizing chip strain. The diagnostics case statistics which show the observed values of strain on chip, against their predicted values is presented in Table 7.

Table 7: Diagnostics Case Statistics Report of Strain on Chip

Standard Order	Actual Value	Predicted Value	Residual	Leverage	Internally Studentized Residual	Externally Studentized Residual	Influence on Fitted Value DFFITS	Cook's Distance	Run Order
1	0.039	0.039	1.361×10^{-4}	0.670	0.155	0.147	0.209	0.005	19
2	0.033	0.034	-9.923×10^{-4}	0.670	-1.129	-1.147	-1.633	0.259	8
3	0.020	0.019	8.941×10^{-4}	0.670	1.018	1.020	1.452	0.210	20
4	0.024	0.024	1.575×10^{-5}	0.670	0.018	0.017	0.024	0.000	15
5	0.026	0.025	7.709×10^{-4}	0.670	0.877	0.866	1.234	0.156	17
6	0.018	0.018	-1.074×10^{-4}	0.670	-0.122	-0.116	-0.165	0.003	10
7	0.030	0.028	1.779×10^{-3}	0.670	2.025	2.500	*3.56	0.831	1
8	0.032	0.031	6.506×10^{-4}	0.670	0.740	0.723	1.029	0.111	4
9	0.020	0.021	-1.749×10^{-3}	0.607	-1.826	-2.122	*-2.64	0.516	13
10	0.020	0.019	6.369×10^{-4}	0.607	0.665	0.645	0.802	0.068	16
11	0.033	0.033	4.938×10^{-4}	0.607	0.515	0.496	0.616	0.041	6
12	0.025	0.027	-1.606×10^{-3}	0.607	-1.677	-1.876	*-2.33	0.435	14
13	0.035	0.034	3.474×10^{-4}	0.607	0.363	0.346	0.431	0.020	11
14	0.027	0.028	-1.460×10^{-3}	0.607	-1.524	-1.650	*-2.05	0.359	7
15	0.024	0.023	8.651×10^{-4}	0.166	0.620	0.600	0.268	0.008	12
16	0.022	0.023	-1.135×10^{-3}	0.166	-0.813	-0.798	-0.356	0.013	18
17	0.021	0.023	-2.135×10^{-3}	0.166	-1.529	-1.657	-0.740	0.047	5
18	0.024	0.023	8.651×10^{-4}	0.166	0.620	0.600	0.268	0.008	2
19	0.024	0.023	8.651×10^{-4}	0.166	0.620	0.600	0.268	0.008	3
20	0.024	0.023	8.651×10^{-4}	0.166	0.620	0.600	0.268	0.008	9

Table 7 shows low residual values, supporting the adequacy of the fitted quadratic model. Accepting the model, however, must be done based on a thorough statistical diagnostic evaluation, verifying residual normality, independence and constant variance. Residual

magnitude and leverage are both different diagnostics, with the former being based on prediction error, and the latter, on unusually high leverage (predictor settings) and possible influence on the fitted estimates. Accordingly, the normal probability plot of residuals for chip strain is

presented in Figure 1 to assess conformity with the normality assumption of the response surface model. If the plotted residuals are close to the reference line, the

model is likely to be adequate, and the residuals are likely to be approximately normally distributed.

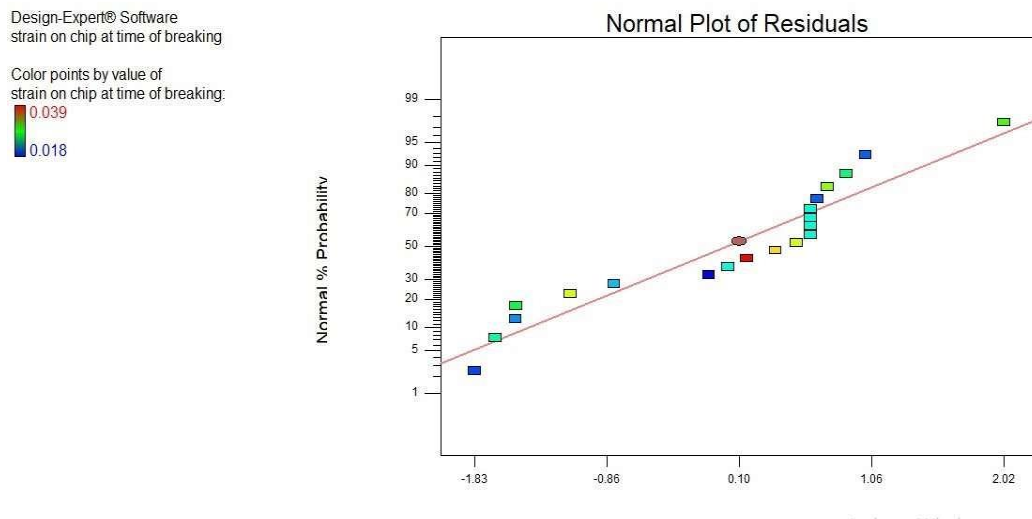


Figure 1: Normal Probability Plot of Studentized Residuals for Strain on Chip

A normal probability plot of studentized residuals was used to evaluate the normality assumption underlying the fitted response surface model. Studentized residuals are residuals divided by their estimated standard deviations, where residuals are the difference between the observed and the predicted values of the chips, and their estimated standard deviations are the estimated standard deviations of the residuals. Residuals are approximately normally distributed when plotted points are approximately linear. The distribution of studentized residuals appeared approximately normal as shown in

Figure 1, which also showed no outstanding observations indicating the developed model is adequate. Cook's distance was also calculated to investigate the impact of each experimental run on the response; the results are shown in Figure 2. Cook's distance measures the distance between the fitted regression estimates of an observation run, compared to the distance between the estimates evaluated without the use of the observation in question; observations with distances that are very large relative to the other runs should carefully be examined as possible influential points

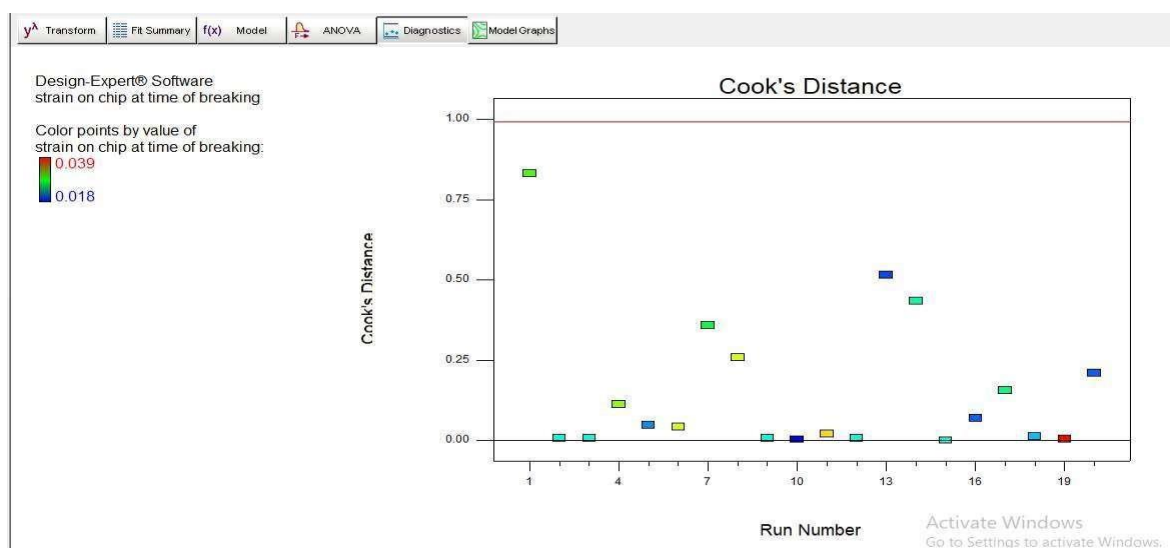


Figure 2: Generated Cook's Distance for Strain on Chip

In studying the effects of combine input variables on the response variable (strain on chip), 3D surface plots presented in Figure 3 were employed.

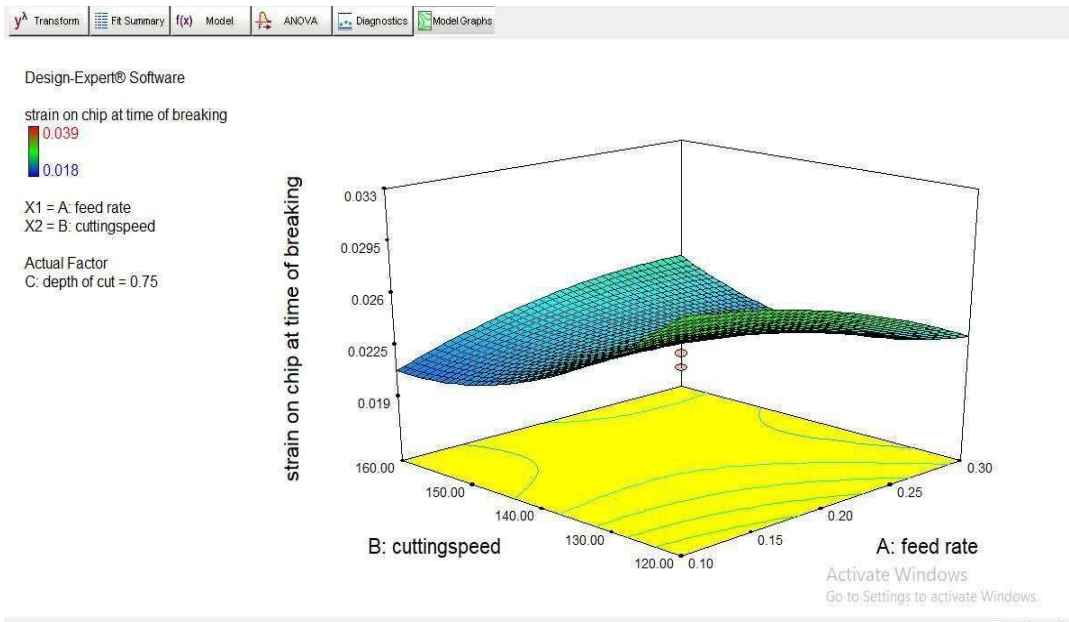


Figure 3: Surface Plot for Measured Strain on Chip, Cutting Speed and Feed Rate

In studying the effects of combine input variables on the response variable (strain on chip), 3D surface plots presented in Figure 4 were employed.

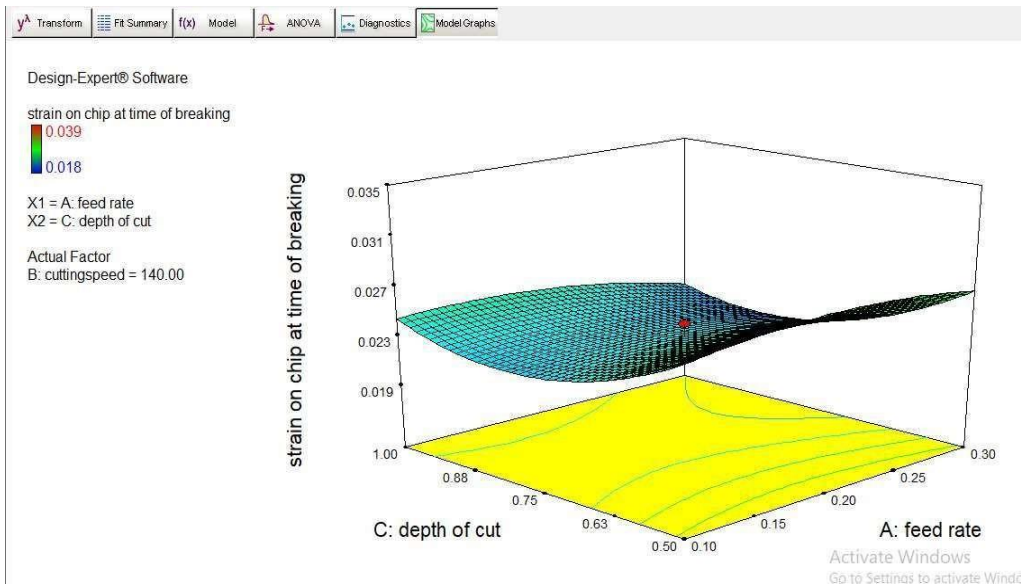


Figure 4: Surface Plot for Measured Strain on Chip, Depth of Cut and Feed Rate

In studying the effects of combine input variables on the response variable (strain on chip), 3D surface plots presented in Figure 5 were employed.

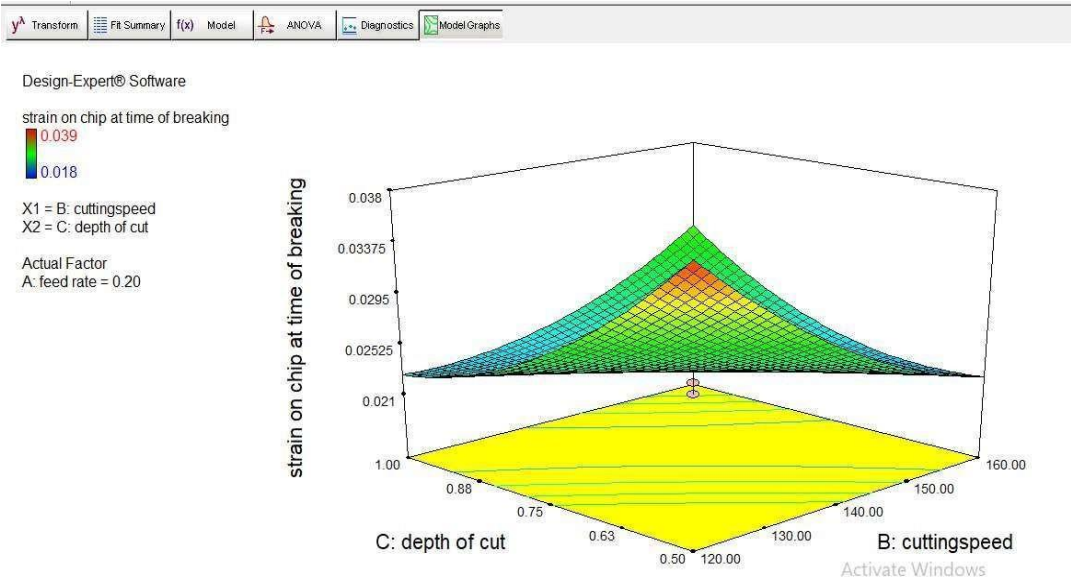


Figure 5. Surface Plot for Measured Strain on Chip, Depth of Cut and Cutting Speed

Numerical optimization was subsequently performed to evaluate overall model desirability. The optimization objective was to identify optimal values of current (A), voltage (V), and gas flow rate (L/min) that minimize chip strain. The numerical optimization interface, including specification of the objective function, is shown in Figure 6.

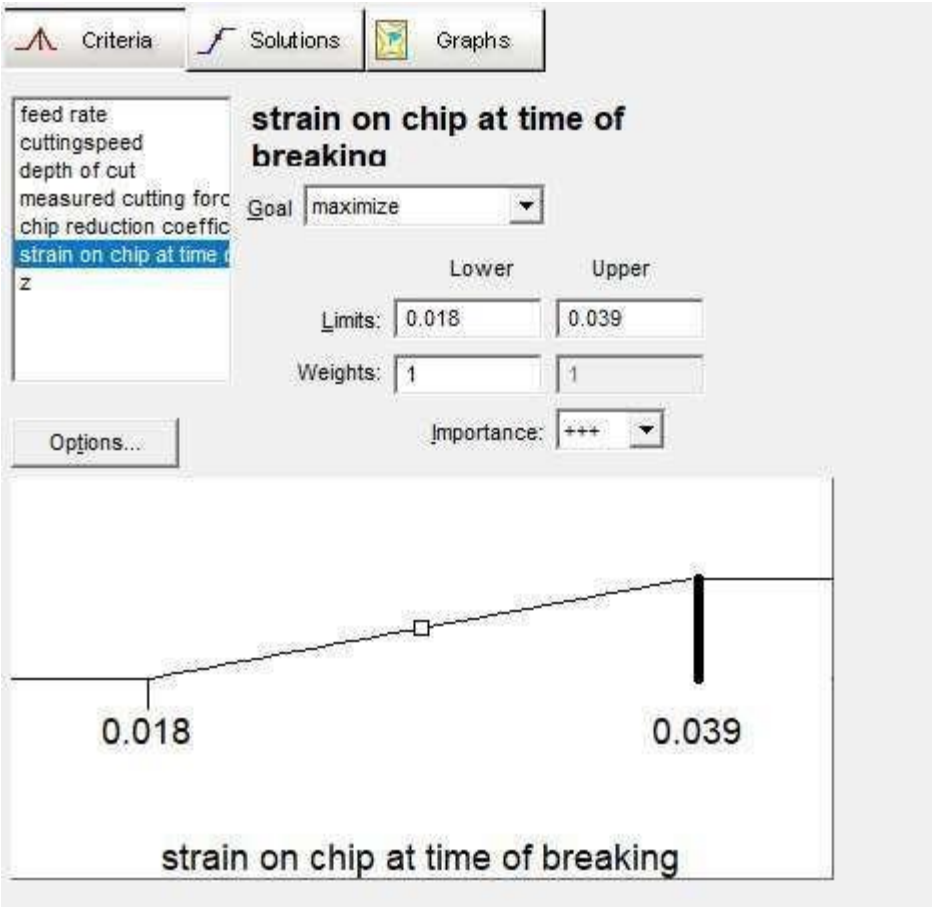


Figure 6: Percentage Dilution for Measured Strain on Chip

The optimization objective for chip strain was minimization, and the relative importance weight was 5.0 for this response. The boundary conditions were set to a desirability value of 1.0 representing the target (minimized) response and of 0.1 representing the least desirable response in the feasible region. This will limit the optimizer to look for parameter values that minimize the attainable value of strain. Based on the optimal solution

derived, contour plots are generated and shown in Figures 7, 8 and 9, which are the strains of the chip as a function of a pair of the optimized input variables. These plots help to visualise the response surface in two dimensions so that some regions of operation can be identified where strain is minimised within the given constraints.

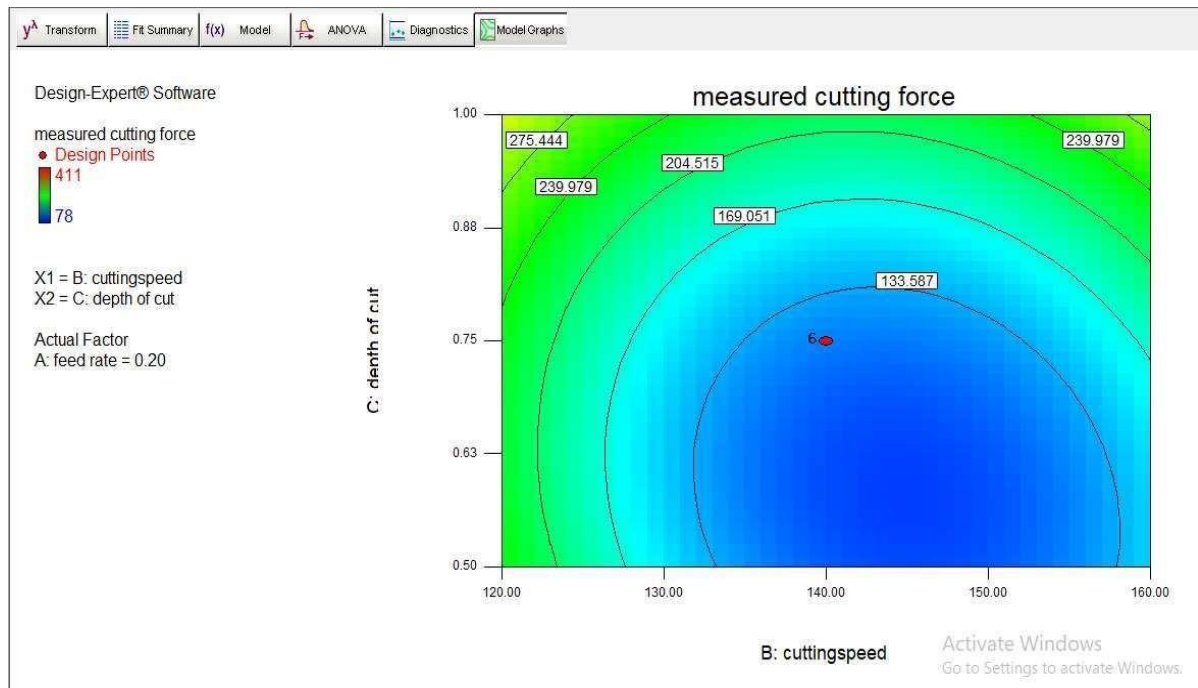


Figure 7: Contour Plots Measured Strain on Chip, Depth of Cut and Cutting Speed

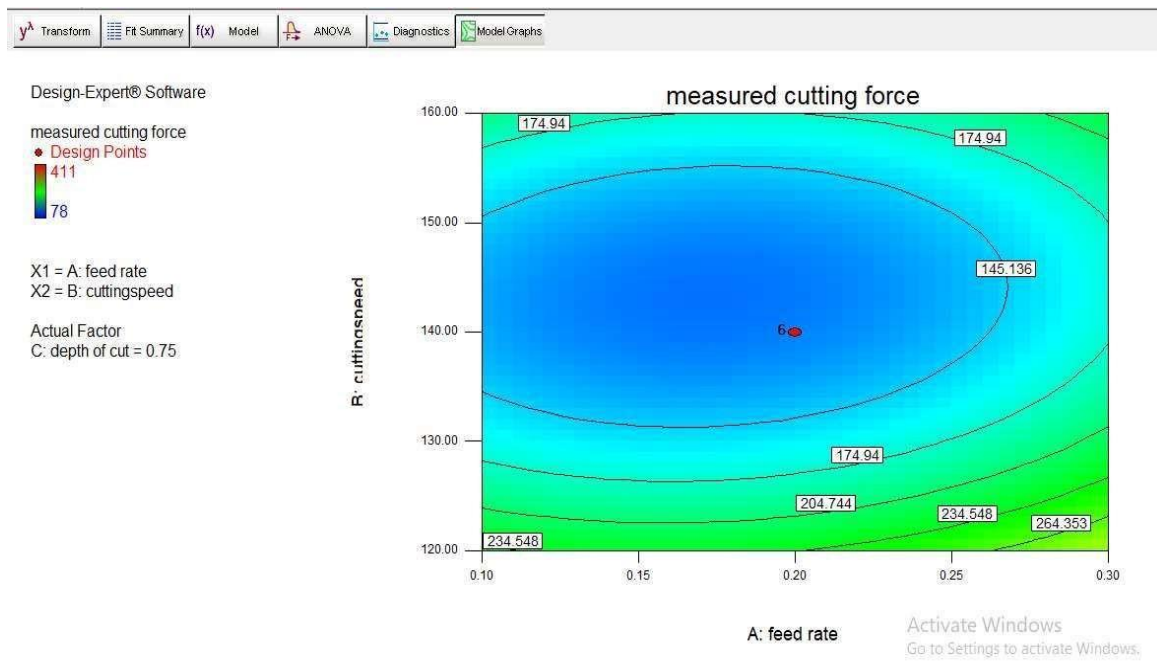


Figure 8: Contour Plots Measured Strain on Chip, Cutting Speed and Feed Rate

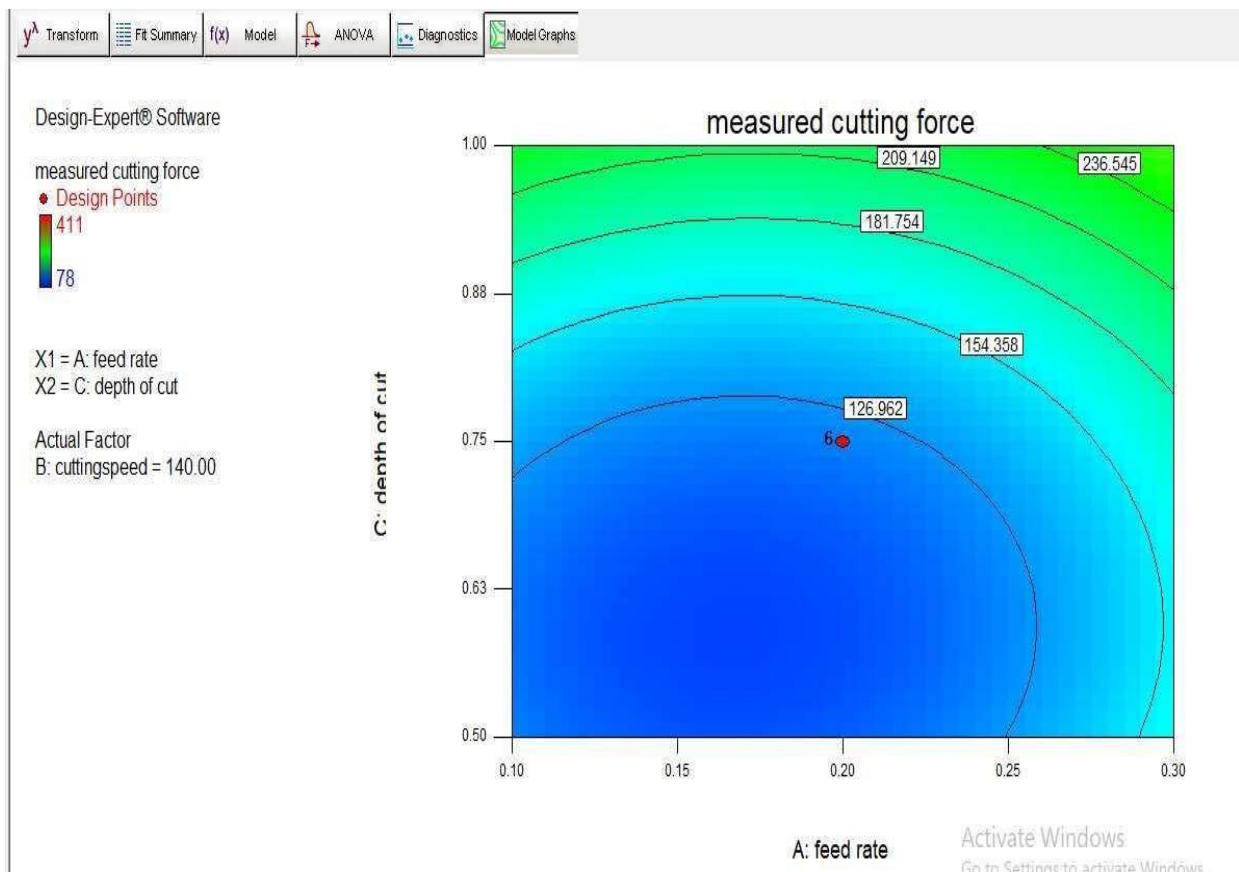


Figure 9: Contour Plots Measured Strain on Chip, Depth of Cut and Feed Rate

3.2 Modelling and prediction using ANN

RSM coupled with numerical optimization proved effective in identifying optimal values of depth of cut, cutting speed, and feed rate that minimize chip strain, as well as in quantifying the underlying mathematical relationships between input factors and response. A well-known drawback of RSM is the limited predictive ability beyond the range of experimental conditions defined by the design of experiments: the performance of the model depends on the quality and extent of the experimental design. An ANN model was developed to extend the prediction capability beyond the tested factor space. Prior to network training, experimental data were normalized to a common scale. This preprocessing step reduces weight-instability problems that can result in over training, which is one of the main concerns with neural network modelling, as larger inputs will not dominate the learning

of the weights. The architecture of the ANN and a portion of the experimental data are depicted in Figure 10. Measured chip strain is represented by the output node (Out1), and cutting speed, feed rate and depth of cut are represented by the three input nodes (In1, In2, In3), respectively. Figure 11 presents the same data after normalization, where it is transformed to a common scale and all the inputs contribute equally to the learning of weights during training, validation and testing. The network structure (the number of hidden layers, neurons per hidden layer and the training algorithm chosen) is also summarized in Figure 11. The ANN was designed to include complex, nonlinear interactions between the machining parameters and mechanical strain of the chip, and was trained to reduce the error in predicting the strain on chip.

Name
network8

Network Properties

Network Type: Feed-forward backprop

Input data: input

Target data: Target

Training function: TRAINLM

Adaption learning function: LEARNGDM

Performance function: MSE

Number of layers: 2

Properties for: Layer 1

Number of neurons: 10

Transfer Function: TANSIG

Figure 10: Network Properties

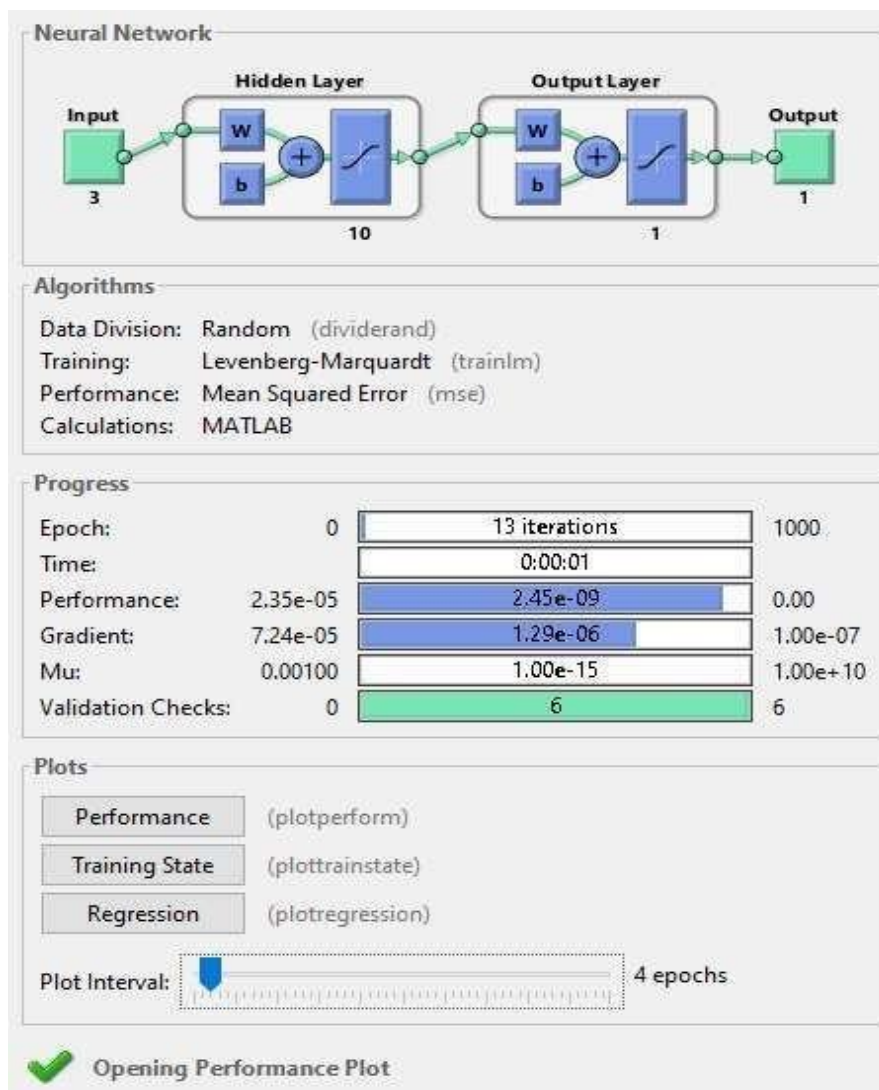


Figure 11: Model Summary for Predicting Strain on Chip

The performance curve for the trained network to predict the strain on chip is shown in Figure 12. It illustrates the mean squared error plotted against the number of epochs. The curve shows the relationship between the convergence of training, validation and test sets. The validation error is seen to closely follow the training error with no significant deviation. The best

validation performance is indicated at the point where the error is minimized before the onset of potential overfitting. The model has been shown to yield high fidelity predictions of lower force regimes, which is a good representation of the target criterion of measured strain on chip equal to minimum.

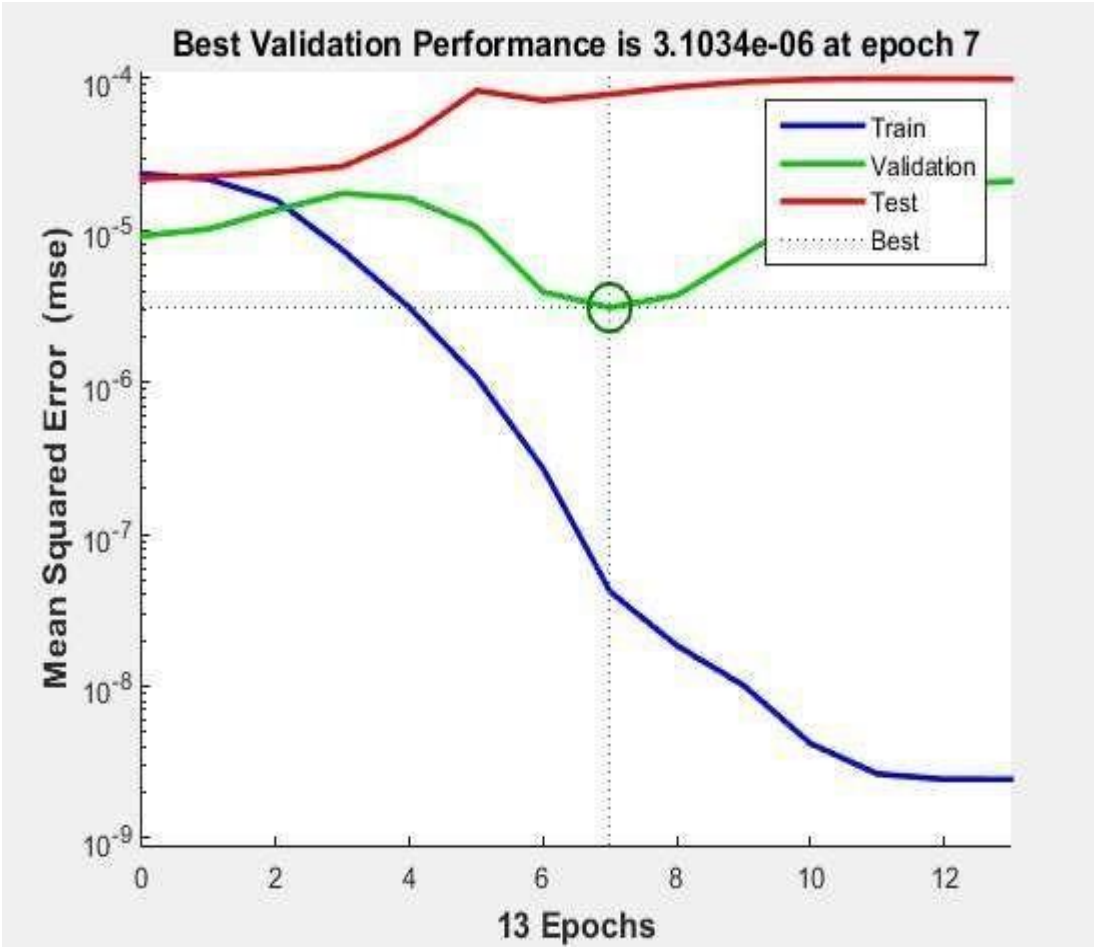


Figure 12. Performance Curve of Trained Network for Predicting Strain on Chip

The training state of the neural network for predicting strain on chip is shown in Figure 13. This is the visualization of state plots, the learning rate parameter μ , and validation checks. The figure confirms stability of the training algorithm. The gradient gradually reduces down to a minimum. This means successful optimization

of the weights from In1 (depth of cut) to out1 (strain on chip) and from In2 (cutting speed) to out1 (strain on chip) and from In3 (feed rate) to out1 (strain on chip). The validation checks demonstrate appropriate stopping of training before the network started to “memorize noise” in the normalized data set.

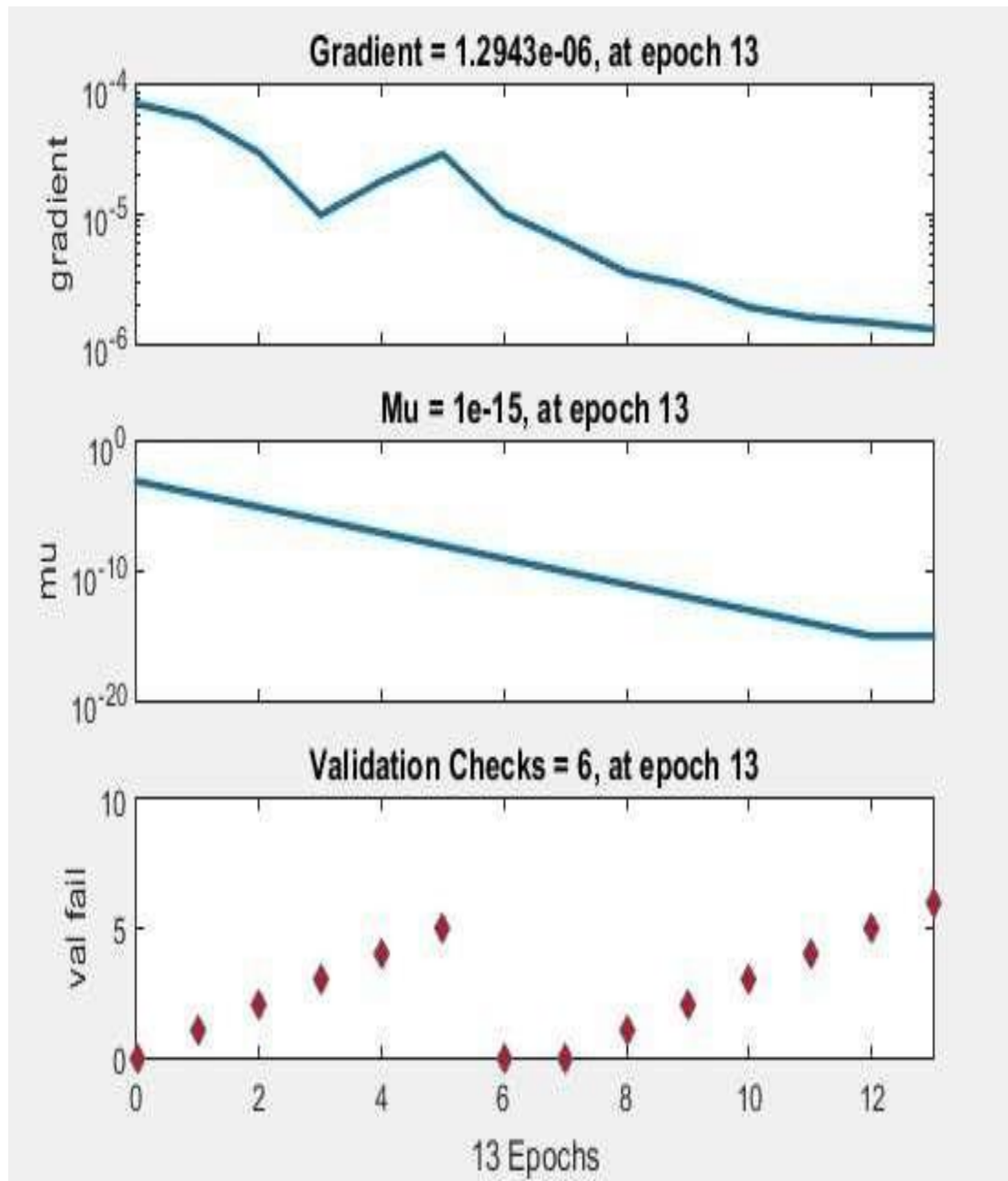


Figure 13: Neural Network Training State for Predicting Strain on Chip

Figure 14 displays the regression plot showing the progress of training, validation, and testing. The scatter plot of network outputs versus experimental targets for the prediction of strain on chip demonstrates a strong linear correlation across all phases of data handling. The tight clustering of data points along the fit line indicates that the

normalized model accurately captures the variance in strain on chip as a function of current, voltage, and gas flow rate. The high correlation coefficient attests that the model is robust and free from the limitations of weight variation that typically affects neural network performance.

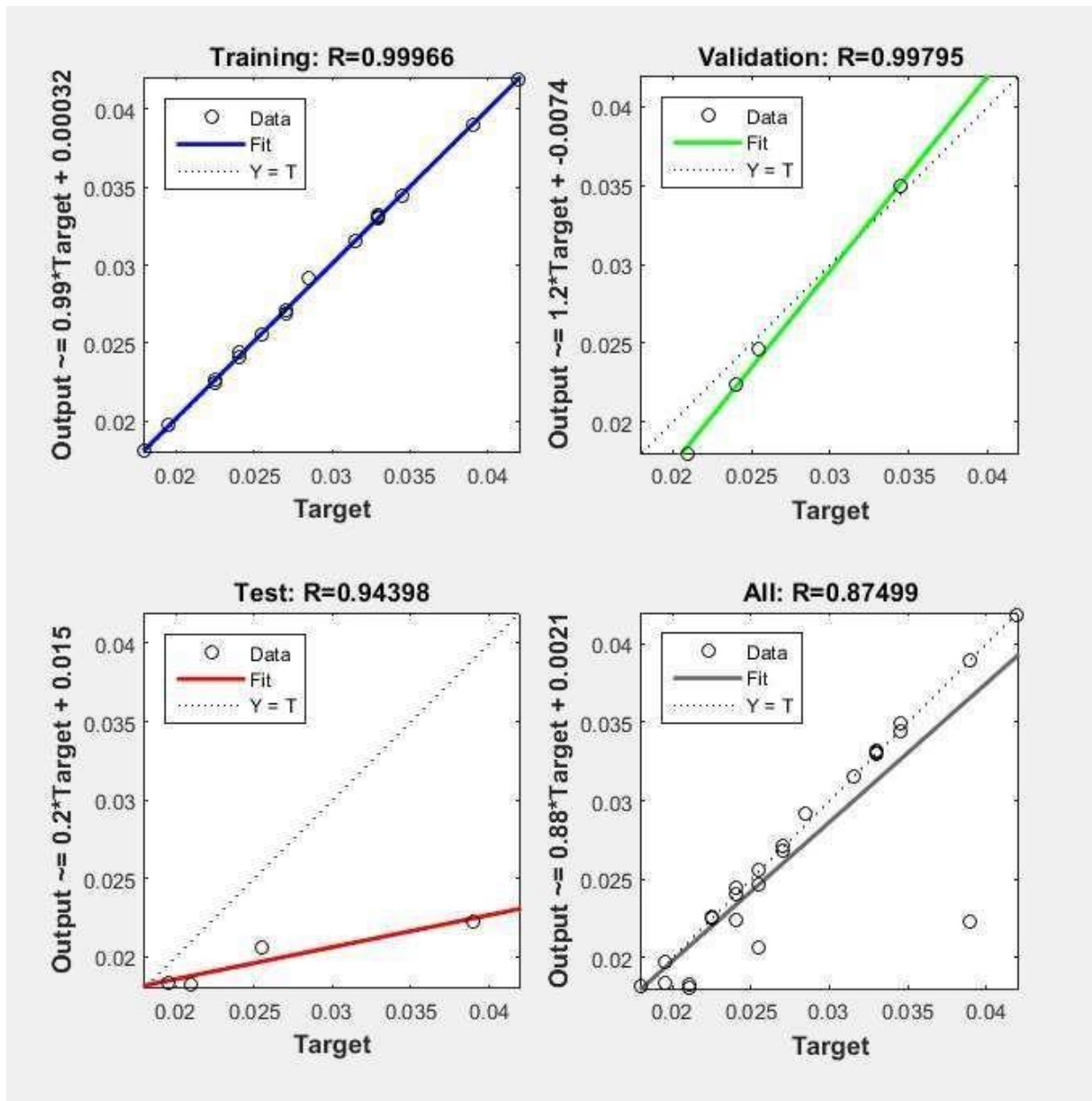


Figure 14: Regression Plot Showing the Progress of Training, Validation and Testing

4.0 Conclusion

The present study has successfully developed predictive models for strain on chip at the time of breakage during dry drilling of mild steel. According to the study, the BC interaction (cutting speed $\times$ depth of cut) is overwhelmingly dominant ($F = 110.69$, $p < 0.0001$). High-speed, deep-cut dry drilling should be avoided to prevent catastrophic strain accumulation. The 2nd order polynomial RSM model provides exceptional predictive capacity ($R^2 = 0.9627$, Adj. $R^2 = 0.9291$, Adeq Precision = 19.198). The optimal strain of 0.0253804 (approximately

2.5% of workpiece reference strain) is achieved at feedrate 0.30 mm/rev, cutting speed 146.22 m/min, and depth of cut 0.50 mm with 93.1% desirability which provides a wide safety margin below the 15% breakage threshold. ANN prediction for strain ($R^2 = 76.56\%$) shows that strain is nonlinear and larger datasets and more complex network architectures may improve its performance. The following conclusions can be deduced from the study:

- The present study demonstrates that chip strain

can provide an effective early-warning indicator of tool breakage during dry drilling. The interaction between cutting speed and depth of cut showed the strongest influence on chip strain, amongst other investigated parameters.

(ii) The quadratic RSM model provided a strong representation of chip-strain behaviour and showed superior predictive performance compared with the developed ANN model under the investigated conditions.

(iii) The optimization analysis identified a minimum predicted chip strain, at a specific feed rate, cutting speed, and depth of cut. This operating condition provides a practical basis for selecting drilling parameters that limit strain accumulation and reduce the likelihood of tool-breakage conditions.

The study contributes to the advancement of predictive machining and tool-condition monitoring by introducing chip strain as a direct response for assessing the onset of tool-breakage conditions. By combining RSM-based statistical modelling with ANN prediction and numerical optimization, the present study provides a framework for understanding, predicting, and controlling chip-strain behaviour during dry drilling. The findings provide a basis for incorporating chip-strain monitoring into proactive tool-breakage prevention. Further research should focus on validating the optimized condition experimentally, and evaluating optical or acoustic sensing approaches for real-time chip-strain monitoring.

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