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Prediction of tool wear using regression and artificial neural network models in end milling of AISI 304 Austenitic Stainless Steel

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Abstract -Tool wear prediction plays an important role in industry for higher productivity and product quality. Flank wear of cutting tools is often selected as the tool life criterion as it determines the diametric accuracy of machining, its stability and reliability. This paper focuses on two different models, namely, regression mathematical and artificial neural network (ANN) models for predicting tool wear. In the present work, flank wear is taken as the response (output) variable measured during milling, while helix angle, spindle speed, feed rate and depth of cut are taken as input parameters. The Design of Experiments (DOE) techniques developed for four factors at five levels to conduct experiments. Experiments have been conducted for measuring tool wear based on the DOE technique in a vertical machining center on AISI 304 steel using solid carbide end mill cutter. The experimental values are used in Six Sigma software for finding the coefficients to develop the regression model. The experimentally measured values are also used to train the feed forward back propagation artificial neural network (ANN) for prediction of tool wear. Predicted values of response by both models, i.e. regression and ANN are compared with the experimental values. The predictive neural network model was found to be capable of better predictions of tool flank wear within the trained range.

***Keywords:* AISI 304 steel, Artificial Neural Network, Helix angle, Regression model, Tool wear.**

I. INTRODUCTION

The productivity of a machining system and machining cost, as well as quality, the integrity of the machined surface and profit strongly depend on tool wear and tool life. Sudden failure of cutting tools leads to loss of productivity, rejection of parts and consequential economic losses. Flank wear occurs on the relief face of the tool and is mainly attributed to the rubbing action of the tool on the machined surface. The flank wear predominantly occurs in cutting tools, so the life of a particular tool used in the machining process depends upon the amount of flank wear. But the crater wear is prevalent only under certain cutting conditions, i.e. higher spindle speeds and feeds lead to more crater wear. In this case, tool life is evaluated by means of crater wear. As the flank face of the cutting tool performs a rubbing action against the work piece materials, the surface finish of the machined work piece primarily depends upon the amount of flank wear. An increase in the amount of flank wear leads to a reduction in nose radius of the cutting tool, which in turn reduces the surface finish. The dominating wear mode for the tools considered in this work is excessive flank wear, which gives increased cutting forces and vibrations in the milling process. The maximum utilization of cutting tool is one of the ways for an industry to reduce its manufacturing cost. Hence, tool wear has to be controlled and should be kept within the desired limits for any machining process. Tool wear mainly depends upon the machining parameters used for milling of a particular work piece material. In order to maximize gains from a manufacturing process, an accurate process model must be constructed for an end milling process with helix angle, spindle speed, feed rate and depth of cut as input machining parameters and tool flank wear as the output variable. Experiments have been conducted to measure tool wear based on Design of Experiments (DOE) for five level four factors full factorial technique. Design of Experiments (DOE) is a scientific approach of planning and conducting experiments to generate analyze and interpret data so that valid conclusions can be drawn efficiently and economically. After determining the significant coefficients using Quality America DOE PC- IV, the final regression model is constructed to predict the tool wear. The value of the regression coefficients in the regression model gives an idea as to what extent the control variables affect the responses quantitatively. The accuracy of the model has been tested using the analysis of variance techniques (ANOVA). The regression mathematical model has been used to plot the interaction graphs for different combinations of machining parameters .The validity of the final regression models is further tested using the ANN model, which compares measured and predicted values. Knowledge of tool wear will help the operator in selecting machining parameters to minimize tool wear.

II. LITERATURE SURVEY

Palanisamy et al. [1] developed a regression and artificial neural network mathematical model to predict tool flank wear in terms of machining parameters such as cutting speed, feed and depth of cut. Predicted values of tool flank wear of the mathematical model compared with the experimental values. Prickett and Johns [2] presented an overview of approaches to end milling tool monitoring techniques for the detection of cutting tool wear and

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breakage during the milling process. Yongjin and Fischer [3] developed tool wear index (TWI) and the tool life model for analyzing wear surface areas and material loss from the tool using micro-optics and image processing/analysis algorithms. They proposed optimal control strategy demonstrates how production cost can be minimized by adjusting machining parameters and extending the tool usage within the constraints for specific machining conditions. Oraby and Hayhurst [4] developed models for wear and tool life determination using non linear regression analysis techniques in terms of the variation of a ratio of force components acting at the tool tip. Choudhury et al. [5] predicted the response variables flank wear, surface finish and cutting zone temperature in turning operations using Design of Experiments and the neural network technique and the values obtained from both methods were compared with the experimental values of the response variables to determine the accuracy of the predictions. Srinivas and Kotaiah [6] developed a neural network model to predict tool wear and cutting force in turning operations for cutting parameters cutting speed, feed and depth of cut. Chattopadhyay [7] has used the forward back propagation artificial neural network for evaluation of wear in turning operations using carbide inserts taking speed, feed and depth of cut as input parameters. Recently Sivasakthivel et al. [8] developed a mathematical model to prediction of tool wear from machining parameters by response surface methodology in end milling. In his work the author selected a input parameters are helix angle, spindle speed, feed rate, axial depth of cut and radial depth of cut to study the effect of the parameters using tool wear model in AI 6063 material with high speed steel end mill cutter. Prediction of tool wear is an important study in metal cutting in order to maximize the utilization of the tool and minimize the machining cost. In order to maintain the tool life, the proper setting of machining parameters is crucial before the process takes place. The user of the machine tool must know how to choose cutting parameters in order to minimize tool wear.

The main goal of this work is to study the influence of cutting conditions such as helix angle, spindle speed, feed rate, and depth of cut on tool wear in the end milling process. In order to increase the efficiency and reduce the cost of machining, it is necessary to improve understanding the metal cutting process. The regression and ANN models have been developed to predict tool wear in end-milling. Researchers have used many methods to predict tool wear, but comparisons of these methods have not been done for milling in the above cutting conditions. In the present work, the predictions from the regression and ANN models are compared with the experimental results to determine prediction accuracy.

III. ROLE OF FLANK WEARS IN TOOL LIFE EVALUATION

Tool wear can be categorized into several types as crater wear, notchwear, chipping; plastic deformation, ultimate failure and flank wear based on the tool wear phenomena. In practice flank wear is used to determine the tool life. Wear on the relief face is called flank wear and it occurs due to abrasive wear of cutting tool against the machined surface. Flank wear is mainly attributed to the rubbing action of the tool on the machined surface. The flank wear predominantly occurs in the cutting tool, so the life of a particular tool used in a machining process depends upon the amount of flank wear. If the amount of flank wear increases, a reduction in nose radius of the cutting tool occurs, this in turn reduces the surface finish of the product. Among the aforesaid wears, the principal flank wear is the most important because it raises the cutting forces and related problems. ISO standard 3685 [9] dictates that the end of useful tool life is determined when a tool ceases to produce a desired part size and surface quality. In this work, the flank wear is only considered to evaluate the tool condition during the machining process. The life of the tool is estimated by flank wear.

IV. RESPONSE SURFACE METHODOLOGY (RSM)

Response surface methodology is one of the most informative methods to of analyze the result of a factorial experiment. The present work considers helix angle of cutting tool, spindle speed, feed rate and depth of cut as the process parameters: while the tool wear is taken as a response variable (Table 1). The response, tool wear (T) can be expressed as a function of process parameters helix angle (α), spindle speed (S), feed rate (F) and depth of cut (D) as shown in equation (1) below Tool wear (T) = ψ (αiu, Siu, Fiu, Diu) + eu (1)

Where ψ = response surface, eu = residual, u = no of observations in the factorial experiment and iu represents level of the ith factor in the uth observation.

When the mathematical form of ψ is unknown, this function can be approximated satisfactorily within the experimental region by polynomials in terms of process parameter variable. A central composite Rota table design was chosen as the design matrix to conduct the experiments. This design matrix [10] comprised of a full replication of 24 (=16) factorial design plus seven centre points and eight star points, as given in Table 2. While all machining parameters at the intermediate levels (0) constituted the centre points and the combination of each machining parameters at either its highest value (+2) or lowest value (−2); the other three parameters of the intermediate levels (0) constituted the star points. Thus,

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the 31 experimental runs allowed the estimation of linear, quadratic, and two-way interactive effects of the process parameters on surface roughness. The upper limit of the parameter has been coded as 2, lower limit as -2 and the coded values for intermediate values were calculated from equation (2) given below [11]. Table 1& 2 is shown in Appendix.

V. EXPERIMENTAL SETUP

Machining experiments have been carried out in a HAAS vertical machining center as per the design matrix on AISI 304 Austenitic Stainless Steel work piece using an uncoated solid carbide end mill cutter with a diameter of 12 mm and having 4 flutes. The dimensions of the work piece specimen were 32 mm X 32 mm in cross section and 50 mm in length and its chemical

$$X_i = \frac{2(2X-(X_{\max}+X_{\min}))}{(X_{\max}-X_{\min})} \quad (2)$$

Where, Xi– The required coded value of a variable X

X– Is any value of the variable from Xmin to Xmax
Xmin – Is the lower limit of the variable
Xmax – Is the upper limit of the variable

The intermediate values coded as -1, 0, and composition is shown in Table 3. The machining operations were carried out as per the conditions given by the design matrix at random to avoid systematic error. The tool wear was measured by using Metzer tool maker's microscope on the flank surface of the end mill cutter specimen. The photograph of the experimental set-up is shown in Figs 1-2.

Table 3 Chemical composition of AISI 304 material:

C	Si	Mn	P	Cr	Mo	Ni	Cu	V	Fe
0.027	0.0278	1.53	0.015	18.7	0.06	8.59	0.096	0.015	70.68

Fig.1 Experimental set up of vertical machining center

Fig. 2 Metzer Tool maker's microscope.

VI. DEVELOPMENT OF MATHEMATICAL MODEL

The general form of a quadratic polynomial which gives the relation between response surface 'y' and the process variable 'x' under investigation is given in equation Where a0 = constant, ai = linear term coefficient, aii = quadratic term coefficient and aij = interaction term coefficient. The values of the coefficients of the polynomials were calculated by multiple regression method. Statistical software Quality America (QA) Six Sigma DOE PC- IV [12] was used to calculate the values of these coefficients. The second order mathematical model was developed by neglecting the insignificant coefficients of the tool wear (T) are given in equation (4).

Tool wear (T) = $0.152-0.042\alpha+0.043 S+0.019F+0.068D+0.031\alpha^2+0.029 S^2+0.026 F^2+0.037D^2- 0.004\alpha F-0.024\alpha D-0.014FD$ (4)

$$Y = a_0 + \sum_{i=1}^{4} aiXi + \sum_{i=1}^{4} aiiXi^2 + \sum_{i<j}^{4} aijXiXj$$

Where
α = Helix angle (°), S = Spindle speed in rpm
F= Feed rate in mm/rev, D = Depth of cut in mm

VII. CHECKING THE ADEQUACY OF THE DEVELOPED MODEL

The adequacy of the model has been tested using the analysis of variance techniques (ANOVA). As per this ANOVA technique the calculated value of the F-ratio of the model developed should not exceed the standard tabulated value of the F-ratio for a desired level of confidence (say 95%), and if the calculated value of the R-ratio of the model developed exceeds the standard tabulated value of the R- ratio for the desired level of confidence (say 95 %), then the model may be considered adequate within the confidence limit [13]. From Table 4, it is found that the model is adequate. It is evident from the table 3 that the error between the experimental value and predicted value is less than 5%. Table 4 is shown in Appendix..

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VIII. RESULT AND DISCUSSION

Strong interactions were observed between process parameters for tool wear, the most significant interaction effects were analyzed. The regression mathematical model has been used to plot interaction graphs for different combinations of machining parameters and effects were analyzed.

A. INTERACTION EFFECT OF HELIX ANGLE AND FEED RATE ON TOOL WEAR:

Fig. 3 shows the interaction effect of helix angle (α) and Feed rate (F) on tool wear T .From the figure, it is clear that increase in helix angle from 25° to 30° tool wear is decreased . Further increasing helix angle from 30° to 45° increasing the tool wear with increasing of feed rate. It is evident from the fig.3, tool wear is maximum (about 0.25mm) When helix angle (α) and feed rate (F) are at their higher limits (+2) and minimum is (about 0.141mm) When and F is the (-1) limit.

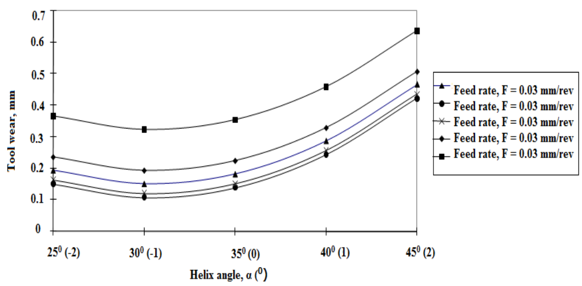

Fig.3 Interaction effect of helix angle and Feed rate

B. INTERACTION EFFECT OF FEED RATE AND DEPTH OF CUT ON TOOL WEAR

Fig.4 shows the interaction effect of feed rate and depth of cut on tool wear. From the fig.3, it is observed that feed rate increases from 0.03mm/rev to 0.06 mm/rev decrease in tool wear for all values of depth of cut. Further increasing the feed rate from 0.06 mm/rev to 0.15 mm/rev increases the tool wear for all values of depth of cut. Tool wear tends to increase with increasing depth of cut. When the depth of cut is lower, there is less work piece material adhered to the flank than at larger depth of cut. Since the heat and the forces generated during the cutting process are higher at larger depth of cut, it is reported that the higher temperature and the higher force are the main reasons that cause the adhesion of work piece material onto the tool flank face, thus accelerating the tool wear. It is evident from the figure 3 tool wear is maximum (about 0.221 mm) when feed rate and depth of cut are at their higher limits (+2) and is minimum (about 0.124 mm) when feed rate and depth of cut are at their second limits (−1).

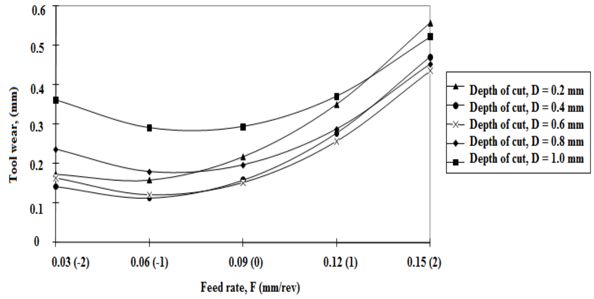

Fig.4 Interaction effect of feed rate and depth of cut

C. Interaction effect of helix angle and spindle speed on tool wear

Fig 5 shows the interaction effect of helix angle α and spindle speed S on tool wear T. From the fig.5, it is clear that helix angle increases from 25° to 30° decreases the tool wear for the spindle speed value upto 1400 rpm. Further increasing the helix angle from 30° to 45° tool wear tends to increase with increasing spindle speed. It has been reported by Eldem et al. [14] that increase in spindle speed accelerates thermally activated wear mechanisms in addition to generating more intense mechanical impact. These promote an increase in the thermal gradient which tends to increase tool wear as thermal crack generation rate increases [15]. The tendency of tool wear to increase with increasing cutting is found to be predominant. It is evident from the fig.5 tool wear is maximum (about 0.418 mm) when α and S are at their higher limits (+2) and is minimum (about 0.135 mm) when α and S are at their limits (−1). Among the various machining parameters, the spindle speed has more effect on tool wear because increase spindle speed accelerates thermally activated wear mechanisms. An average flank wear height of at least 0.3 mm or the maximum wear height of 0.6 mm was considered to be a worn edge. This limit was selected in accordance with the criteria recommended by ISO 8688 which defines effective tool life for carbide tools [16]. Knowledge about tool wear variation helps the operator in selecting suitable machining parameters in order to minimize tool wear.

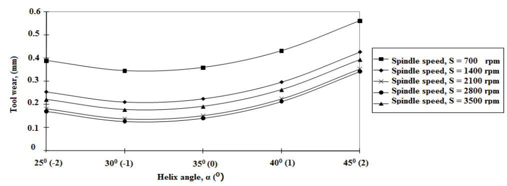

Fig.5. Interaction effect of helix angle and spindle speed

IX. ARTIFICIAL NEURAL NETWORK (ANN)

Artificial neural networks are powerful tools for the identification of systems typically encountered in the

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structural dynamics field. Artificial neural networks have been originally developed to simulate the function of the human brain or neural system. Artificial neural networks are massive parallel-interconnected networks that consist of basic computing elements called neurons interconnected via unidirectional signal channels called connection that imitates the human brain. Each processing element has a single output connection that branches into as many collateral connections as desired. Each neuron carries the same signal —the processing output signal. It has the capability to organize its structural constituents, known as neurons, to perform certain computations many times faster than the fastest digital computer in existence today through a process of learning. Neural networks are physical cellular systems, which can acquire, store and utilize experimental knowledge. In the present paper, the most widely used technique, the feed forward back propagation neural network, is adapted for the prediction of tool wear in the end-milling operation. It is a gradient descent error-correcting algorithm, which updates the weights in such a way that the network output error is minimized [17]. The feed forward back propagation network consists of an input layer (where the inputs of the problem are received), hidden layers (where the relationship between the inputs and outputs are determined and represented by synaptic weights) and an output layer (which emits the outputs of the problem). Training of an ANN plays a significant role in designing the direct ANN-based prediction. The accuracy of the prediction depends on how it is trained. The training of the neural network using a feed-forward back propagation algorithm has been carried out. The network performs two phases of data flow. First the input pattern is propagated from the input layer to the output layer and, as a result of this forward flow of data, it produces an output. Then the error signals resulting from the difference between the computed and the actual are back propagated from the output layer to the previous layers for them to update their weights. The number of neurons in the hidden layer is intentionally chosen to start with one neuron and hidden neurons are added to the hidden layer incrementally. The addition of hidden neurons continues until there is no further improvement in network performance. The accuracy of the network was evaluated by mean sum of squared error (MSE) between the measured and the predicted values for the training. The feedback from that processing is called the "average error" or "performance". Once the average error is below the required goal, the neural network stops training and is, therefore, ready to be verified.

A. TOPOLOGY OF THE NEURAL NETWORK

The topology architecture of feed-forward four layered back propagation neural network is illustrated in Fig.6. The foundation of a neural network is the neuron, which is also called as node or neurode. In a standard architecture, neurons are grouped into different layers including the input, hidden and output layers. The ANN configuration is represented as 4:5:1, that is, the input layer consists of four inputs, the hidden layer five neurons and the output layer one output. The number of neurons in the input layer consists of helix angle, spindle speed, feed rate and depth of cut, which are used to assess the tool wear of the end-milling process. The number of neurons in the hidden layer is determined by investigating many different neural networks, but finally five hidden layers have been selected as an optimum number. There is no fixed rule for determining the number of neurons in the hidden layer. The number of neurons in this layer must be large enough to allow for enough partitions of the non-linear evaluation space. The number of output nodes is taken to be one, so as to indicate the value of tool wear.

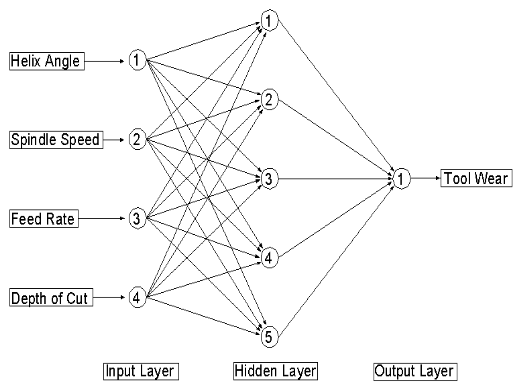

Fig.6. ANN model structure

B. Training the neural network

MATLAB 7.6 has been used for training the network model for tool wear prediction. In the training phase, the values of weights must be initially randomly preset in a chosen range; in this case, from 0 to 0.1. There are 31 training patterns considered for prediction of tool wear. Each neuron is a processing element, which performs a weighed sum of all input variables that feed it. Depending on the value of weighted sum of the variables, the neuron gives a signal to the neurons in the adjacent layer through a non-linear transfer function (sigmoid function in this case). The tool wear of training samples is treated as the desired and target output. The algorithm used for the neural network learning is 'the backward propagation algorithm'. So, the learning has an adaptive nature that means vector pairs from the training model are mapped, respectively, to reinforce the weights until deviation between the training output and the desired output of each training vector sample converges to a negligible error of 0.01 in this application. After the training is completed, the actual weight values are stored in a separate file. The

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weight values are generated using random function. The neural network described in this paper, after successful training, will be used to predict the level of vibration through the acquisition of process value.

The accuracy of the model depends upon the number of neurons in the hidden layer. The accuracy of the model increases as the number of neurons in the hidden layer is increased. The number of neurons in the hidden layer is initially chosen as one, adding neurons to the hidden layer incrementally. The addition of hidden neurons continues until there is no further improvement in network performance. The final optimum architecture/topology is obtained when the number of neurons is five in the hidden layer. The ANN training graph of tool wear for five neurons is given in Fig.7. The predicted values of tool wear by the ANN model are given in Table 3. The predicted values of response by both the models (i.e. regression and ANN model) are compared with the experimental values for the validation set of experiments. This comparison has been depicted in terms of % error in Fig. 8 for validation of the set of experiments. In predicting tool wear the average error by the regression model is less than 5%, whereas it is less than 2% with the ANN model. It is found that the predictive ANN model is found to be capable of better predictions of tool flank wear than the regression model if they had been trained within the range

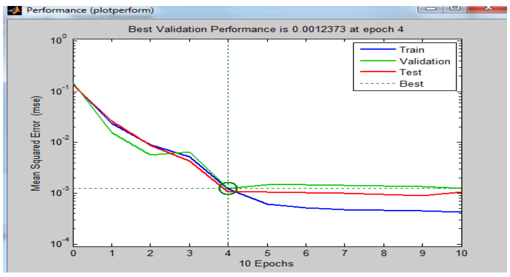

Fig.7 ANN performance graph

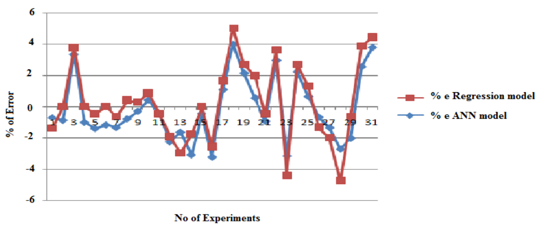

Fig. 8 Comparison of errors in flank wear

X. CONCLUSION

This paper has described the use of Design of Experiments (DOE) for conducting experiments. Two innovative models, regression and artificial neural network (ANN), for predicting tool wear in end milling are presented in this paper. Experiments have been performed to ascertain tool wear in a CNC machining center for machining AISI 304 steel using a solid carbide end mill cutter based on the DOE technique. The experimental values have been used to develop a regression model and feed forward back propagation artificial neural network model for the prediction of tool wear with different numbers of nodes in the hidden layer. The experimentally determined tool wear values are compared with predicted values obtained from the regression and ANN models. The predictive ANN model is found to be capable of better predictions of tool flank wear within the range that they had been trained. The results of the ANN model indicate it to be much more robust and accurate in estimating the values of tool wear when compared with the regression model; it can be used for process modeling for any manufacturing process. The proposed tool wear prediction methods demonstrate how the usage of the tool can be extended by adjusting machining parameters within the constraints for specific machining conditions. This study provides a better position in continuing the tool monitoring system to enable an automated machining process for more efficient manufacturing in the future.

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APPENDIX

Table 1 Machining Parameters and their Levels

Parameters	Unit & Notation	Levels				
		-2	-1	0	1	2
Helix angle	Degree (α)	25	30	35	40	45
Spindle speed	Rpm (S)	700	1400	2100	2800	3500
Feed rate	mm/rev (F)	0.03	0.06	0.09	0.12	0.15
Depth of cut	mm (D)	0.2	0.4	0.6	0.8	1.0

Table 2 Central Composite design matrix

Machining parameters with coded form					Tool wear (mm)			%Error	
Exp no	Helix angle	Spindle speed	Feed rate	Depth of cut	Measured values	Predicted values using regression	Predicted values using ANN	using regressio n model	using ANN model
1	-1	-1	-1	-1	0.144	0.145	0.145	-0.694	-0.694
2	1	-1	-1	-1	0.116	0.117	0.115	-0.862	0.862
3	-1	1	-1	-1	0.239	0.231	0.238	3.347	0.418
4	1	1	-1	-1	0.201	0.203	0.199	-0.995	0.995
5	-1	-1	1	-1	0.216	0.219	0.214	-1.388	0.926
6	1	-1	1	-1	0.173	0.175	0.171	-1.156	1.156
7	-1	1	1	-1	0.301	0.305	0.299	-1.328	0.664
8	1	1	1	-1	0.259	0.261	0.256	-0.772	1.158
9	-1	-1	-1	1	0.356	0.357	0.354	-0.280	0.561
10	1	-1	-1	1	0.234	0.233	0.233	0.427	0.427
11	-1	1	-1	1	0.441	0.443	0.441	-0.453	0
12	1	1	-1	1	0.312	0.319	0.311	-2.243	0.320
13	-1	-1	1	1	0.369	0.375	0.374	-1.626	-1.355
14	1	-1	1	1	0.228	0.235	0.225	-3.070	1.315
15	-1	1	1	1	0.459	0.461	0.457	-0.435	0.435
16	1	1	1	1	0.311	0.321	0.309	-3.215	0.643
17	-2	0	0	0	0.364	0.36	0.362	1.098	0.549
18	2	0	0	0	0.2	0.192	0.198	4	1
19	0	-2	0	0	0.186	0.182	0.185	2.150	0.537
20	0	2	0	0	0.356	0.354	0.351	0.561	1.404
21	0	0	-2	0	0.216	0.218	0.215	-0.925	0.462
22	0	0	2	0	0.303	0.294	0.301	2.970	0.660
23	0	0	0	-2	0.159	0.164	0.161	-3.144	-1.257
24	0	0	0	2	0.446	0.436	0.444	2.242	0.448
25	0	0	0	0	0.153	0.152	0.152	0.653	0.653
26	0	0	0	0	0.151	0.152	0.152	-0.662	-0.662
27	0	0	0	0	0.15	0.152	0.151	-1.333	-0.666
28	0	0	0	0	0.148	0.152	0.151	-2.702	-2.027
29	0	0	0	0	0.149	0.152	0.147	-2.013	1.342
30	0	0	0	0	0.156	0.152	0.154	2.564	1.282
31	0	0	0	0	0.158	0.152	0.157	3.797	0.632

Table 4 Adequacy of the model

Response	Factors df	Lack of Fit- df	Pure Error	F-ratio		R-ratio		Whether model is adequate
				Model	Standard	Model	standard	
Tool wear	11	13	6	19.32	7.79	3.470	7.66	Adequate