International Journal of Latest Research in Engineering and Technology (IJLRET)
ISSN: 2454-5031
www.ijlret.com || Volume 02 - Issue 09 || September 2016 || PP. 01-13

Evaluation of the characteristics of the vibration-assisted tapping process using regression methodology and artificial neural network (ANN)

Swapnil Pawar[*1], Amit Powar[*], Sandip Patil[*] and Dr. Rajkumar Singh[*]
[*]*Kalyani Centre for Technology and Innovation, Bharat Forge Ltd. Pune-411307 India*

Abstract: Abrupt breakage of the taps is repeatedly come across during tapping threads, especially when tapping on difficult to machine material like titanium. In the present study, regression models and artificial neural network (ANN) were developed to predict tapping torque on titanium alloys while performing axial and, axial and torsional vibration-assisted tapping (AVAT and ATVAT). For the development of predictive models, tapping speed, axial vibration amplitude and ratio of forward-backward movement were considered as model variables in both the cases. General full factorial design of experiments was carried out in order to collect torque values and this data is input for model construction. In regression and ANN, different models and algorithms were tested for optimum predictions. The performance of the regression mathematical model and ANN model were compared with experimental outputs. The comparison indicates that the ANN model predictions are closer to the experimental outputs compared to the regression model predictions. This model can be used for predicting the tapping torque and on the basis of this breakage of taps can be avoided. The details of experimentation, model developing strategies, testing, and performance comparisons are presented in the paper.

Keywords: Titanium alloys, vibration-assisted tapping, torque, regression model, ANN.

1. Introduction

Excessive torque is one of the main causes for abrupt breakage of tap inside the predrilled hole during internal thread tapping [1,2]. Nevertheless, it is understood in the earlier investigation that controlled axial [3-8] and torsional [9-14] vibrations in tapping helps to reduce the maximum torque and force to an acceptable level, and eventually improves the tap life. But only a few studies adopt the vibrations variables in analytical models [3,15].

Nowadays machining field is significantly interested in the use of regression analysis and ANN for prediction and analysis of results. This includes studies on surface roughness [16-21], tool wear [18,22-24], tool chip interface temperature [25], heat affected zone [19,26], cutting force [20,27], profile accuracy [28] and cutting tool stress [29] in the earlier publication. The artificial neural network (ANN) is one of the most powerful modeling techniques based on a statistical approach, which has been applied to modeling complicated processes in many engineering fields, such as material science [30], aerospace [31], automotive, energy [32,33] and manufacturing [34]. With ANN, a predictive model can compensate for the limits of conventional predictive control based on the linear model and can predict the non-linear model more accurately. Reddy et al. [35] have shown that an ANN can perform highly complex mappings on nonlinearly related data by inferring subtle relationships between input and output parameters. The basic advantage of ANN is that it is not necessary to postulate a mathematical model at first or identify its parameters. An ANN learns from the data obtained from experiments and recognizes patterns in a series of inputs and output data sets without any prior assumptions about their interrelations. In the past few years, ANN has been developed to model different correlations and phenomena of alloys [31,34,36,37]. Powar and Date [36] have shown that, the ANN can be successfully used in the field of material science for the prediction of the microstructure and mechanical properties of heat treated components with a correlation coefficient (R) over 90%. Malinov and Sha [37] had shown that the fatigue behavior and the corrosion rate can also be predicted as functions of the alloy composition and environmental conditions.

This paper therefore focuses on investigating the suitability of torque predictive models based on regression analysis and ANN. The models for torque prediction were developed with the tapping speed, axial vibration amplitude and ratio of forward-backward movement as the vibration assisted tapping process parameters. The input–output data required to develop both regression models and ANN models have been obtained through multi-level general full factorial design of experiments. The developed models have been tested for their prediction accuracy with new process parameter combinations. The comparison of the main and interaction effects of the process parameters of the regression and ANN models has also been demonstrated in the paper. The details of this work are presented in the following sections of this paper.

2. Experimental Details

The block diagram of the setup employed in the present study to carry axial and torsional vibrations is illustrated in Fig.1. In the present work, piezoelectric device along with generator was used for axial vibrations and CNC controller was used for torsional vibrations. The piezoelectric device was fixed on dynamometer with help of holding fixture and then the whole assembly attached to work table. The tapping was carried out on cylindrical workpieces made of Ti-6Al-4V by right hand taps. The experimental strategy used in this experiment was general full factorial design, as shown in Table 1. In this experiment, there were three controlled variables investigated, including axial vibration amplitude, tapping speed and ratio of forward to backward movement (RFBM) with different level, as shown in Table 2. Each variable had two replications; therefore, the total numbers of experimental trials were 48. This replication permits to obtain more precisely estimate the effect. In this experiment, the orders in which the individual trials of the experiments are to be performed are randomly determined.

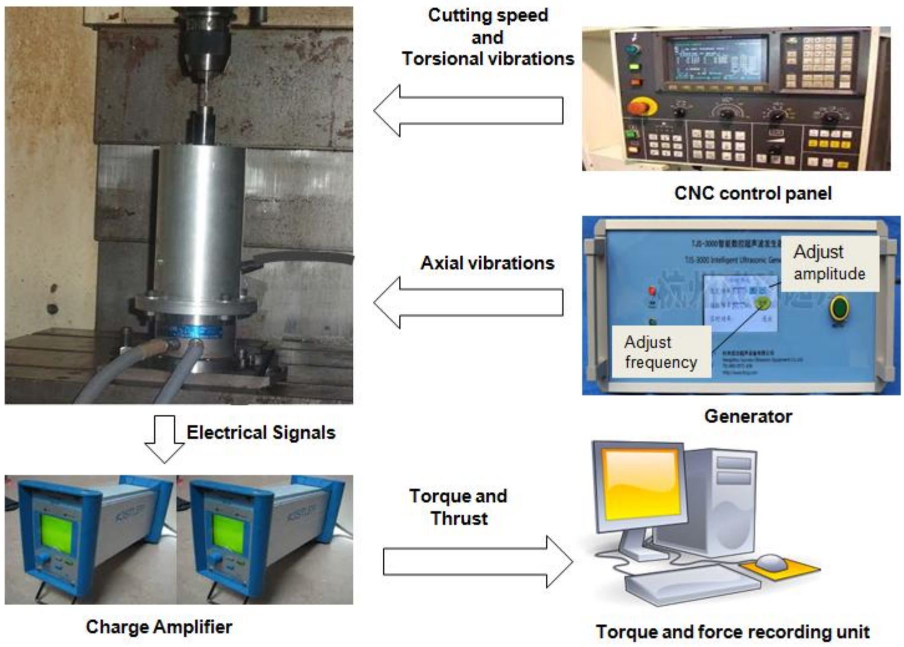


Fig. 1 Experimental setup

Table 1 – Experimental design using general full factorial

Trial no.		Levels of input factors			Response - Torque (N.cm)				
Std. Order	Run Order	Amplitude (µm)	Speed (RPM)	RFBM	Experimental	Regression predication	% error	ANN Predication	% error
26	1	0	50	1.5	148.1	154.0	4.0	152.30	2.76
45	2	14	75	0.0	159.1	153.0	3.9	160.75	1.03
34	3	6	75	1.5	103.1	93.0	9.8	104.15	1.01
40	4	10	75	1.5	93.2	105.2	12.9	94.25	1.11
28	5	0	75	1.5	108.1	118.6	9.8	107.60	0.46
27	6	0	75	0.0	169.9	164.5	3.2	171.50	0.93
32	7	6	50	1.5	143.3	129.7	9.5	142.80	0.35
46	8	14	75	1.5	142.3	140.9	1.0	143.15	0.59
29	9	0	100	0.0	202.4	214.1	5.8	203.85	0.71
41	10	10	100	0.0	172.3	174.3	1.2	171.70	0.35
38	11	10	50	1.5	133.7	142.8	6.8	132.90	0.60
31	12	6	50	0.0	162.1	165.2	1.9	161.65	0.28
33	13	6	75	0.0	126.1	124.4	1.3	125.45	0.52
39	14	10	75	0.0	119.3	127.0	6.4	119.80	0.42
35	15	6	100	0.0	183.3	172.6	5.8	181.70	0.88
44	16	14	50	1.5	183.1	179.3	2.1	184.10	0.54

36	17	6	100	1.5	173.0	145.4	9.4	171.55	0.85
47	18	14	100	0.0	196.1	199.4	1.7	198.90	1.41
25	19	0	50	0.0	209.9	204.0	2.8	210.50	0.29
48	20	14	100	1.5	187.8	191.5	2.0	188.95	0.61
30	21	0	100	1.5	174.3	172.3	1.1	173.50	0.46
37	22	10	50	0.0	153.5	168.6	9.8	153.75	0.16
42	23	10	100	1.5	147.7	156.7	6.1	147.90	0.14
43	24	14	50	0.0	201.3	195.5	2.9	203.05	0.86
11	25	6	100	0.0	180.1	172.6	4.1	181.70	0.88
16	26	10	75	1.5	95.3	105.2	10.4	94.25	1.11
24	27	14	100	1.5	190.1	191.5	0.7	188.95	0.61
10	28	6	75	1.5	105.2	93.0	11.6	104.15	1.01
23	29	14	100	0.0	201.7	199.4	1.1	198.90	1.41
20	30	14	50	1.5	185.1	179.3	3.1	184.10	0.54
3	31	0	75	0.0	173.1	164.5	5.0	171.50	0.93
5	32	0	100	0.0	205.3	214.1	4.3	203.85	0.71
19	33	14	50	0.0	204.8	195.5	4.5	203.05	0.86
21	34	14	75	0.0	162.4	153.0	5.8	160.75	1.03
12	35	6	100	1.5	170.1	145.4	8.7	171.55	0.85
2	36	0	50	1.5	152.3	154.0	1.1	152.30	0.00
7	37	6	50	0.0	161.2	165.2	2.5	161.65	0.28
18	38	10	100	1.5	148.1	156.7	5.8	147.90	0.14
22	39	14	75	1.5	144.0	140.9	2.2	143.15	0.59
9	40	6	75	0.0	124.8	124.4	0.3	125.45	0.52
4	41	0	75	1.5	107.1	118.6	10.8	107.60	0.46
17	42	10	100	0.0	171.1	174.3	1.9	171.70	0.35
14	43	10	50	1.5	132.1	142.8	8.1	132.90	0.60
13	44	10	50	0.0	154.0	168.6	9.5	153.75	0.16
1	45	0	50	0.0	211.1	204.0	3.4	210.50	0.29
8	46	6	50	1.5	142.3	129.7	8.9	142.80	0.35
6	47	0	100	1.5	172.7	172.3	0.2	173.50	0.46
15	48	10	75	0.0	120.3	127.0	5.5	119.80	0.42

Table 2 – Factors and their levels

Factor	Notation	Unit	Level 1	Level 2	Level 3	Level 4
Amplitude	A	µm	0	6	10	14
Tapping Speed	T_s	RPM	50	75	100	--
RFBM	Φ	--	0	1.5	--	--

3. Prediction models

3.1 Regression Model (RM)

The regression examination method has three paths to follow which are experimental investigations, mathematical methods and statistical analysis [38]. A researcher is always keen to put forward the relation between independent variables to govern the optimal solution for objective function with the help of coefficients of the independent variables. These regression coefficients were projected using the experimental data and mathematical methods. In the present investigation, a whole analysis was done using the experimental data in Table 1. Fig. 2 shows a descriptive model building strategy. In the beginning, the best subset regression method is used to analyze the independent variables and their interactions and higher order terms using MINITAB 16 software. This is the most efficient and effective way to develop accurate models with few trams as possible. The purpose of doing this is finding the significance of higher-order terms and kept them as low as possible. Such a low term model is easier to test again in replication as well as in cross-validation studies, less costly to put into practice in predicting and controlling the outcome in the future and easier to understand. Then the models are gauged to finalize the best model by the criteria of standard Error (S), coefficient of determination (R^2), adjusted coefficient of determination ($\underline{R}^2$), and Mallows' C_p statistic. The best subset model is checked with a general regression analysis and further evaluated by t-test, f-test, Durbin-Watson test and residual plots. If model is failing on the tests, go for a next best subset model and repeat the cycle. Finally, the predicted values of regression model are compared with the actual experimental data.

Specially, with a sample of n observations of the dependent variable Y, the regression model [39] can be expressed as,

$$Y(P) = C_0 + \sum_{i=1}^{n} C_i P_i + \sum_{i=1}^{n} \sum_{k=2}^{m} C_{ii} P_i^k + \sum_{1 \le i < j}^{n} C_{ij} P_i P_j + \sum_{1 \le i < j < k}^{n} C_{ijk} P_i P_j P_k + E_r \qquad (1)$$

Where, Y is theresponsevariable (tapping torque), n is the number of factors (3), C_0 is the free term, C_i is the linear effect,C_{ii} is the squared, C_{ij} and C_{ijk} are the interaction effect and E_r is the residual.

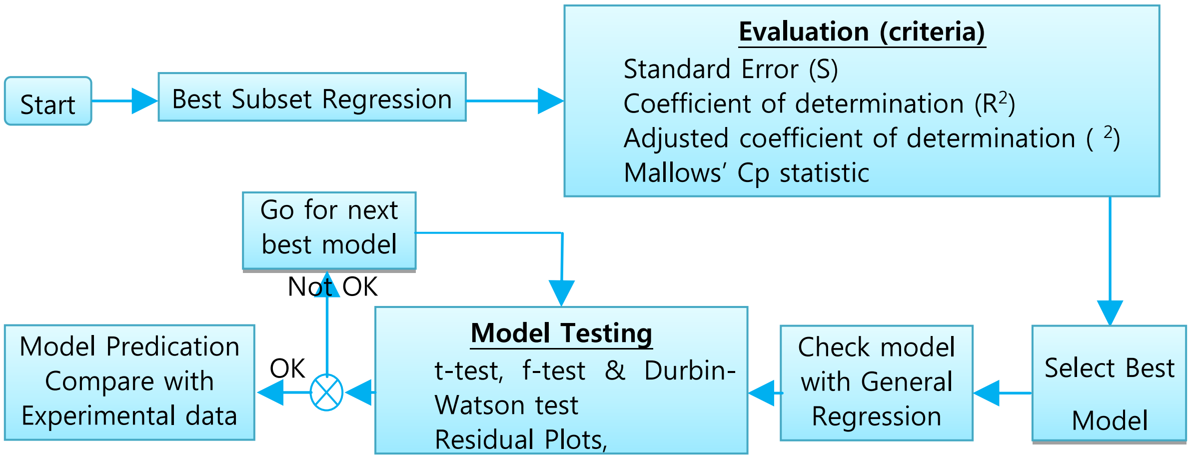


Fig. 2 Regression model building strategy

3.2 ANN model

A typical ANN consists of one input layer, one or more hidden layers and one output layer. ANN learns from given examples by constructing an input-output mapping in order to perform estimations. Each neuron in the input layer represents one independent variable and the neurons in the hidden layers are only for computation purpose. The function of hidden layer neurons is to detect the relationship between network inputs and outputs. Each of the output neuron computes one dependent variable. All the neurons of the network are connected by the weight that expresses the effect of an input set or another process element in the previous layer on the output. The connection weighting and bias values are initially chosen as random numbers and then fixed during the training process. The input layer receives input data and after processing, sends them to the hidden layer. The hidden layer processes the data and sends a response to the output layer. The output layer accepts the response and produces the result.

There are many variations of connections available in literature [40]. However, this study focuses on only one type of network, multilayer perceptron (MLP). The MLP Neural Networks consist of neurons, which are ordered into layers as shown in Fig. 3. The parameters and results of the actual trials shown in Table 1 were used to make a neural network model for the problem. There are several learning algorithms in ANN. A learning algorithm is a procedure of adjusting the weights and biases of a network, to minimize an error between the network output and actual output for a given set of inputs. Back-propagation (BP) algorithm is most popular learning algorithms for multilayer perceptions. However, BP has the disadvantage of slow convergence to the solution and also required long training times. Additionally, success of the BP algorithm depends on the user-dependent parameter [32]. The Levenberg–Marquardt (LM) and Quasi-Newton algorithms are faster than BP algorithm and use standard numerical optimization methods [41]. The LM is an alternative to backpropagation for use in training feedforward neural networks based on a nonlinear optimization. LM algorithms use an approximation of second-order derivatives of the objective function so that better convergence behavior can be obtained. Moreover, this method provides a better parameter change vector than gradient descent technique. Quasi-Newton algorithms build up curvature information at each iteration to formulate a quadratic problem. LM and Quasi-Newton algorithms resolve the some disadvantages of BP mentioned above. ANNs are designed according to their connection architecture, learning the algorithm, the number of hidden layers, number of nodes in a hidden layer and transfer function. Also, these design criteria affect the performance of ANNs.

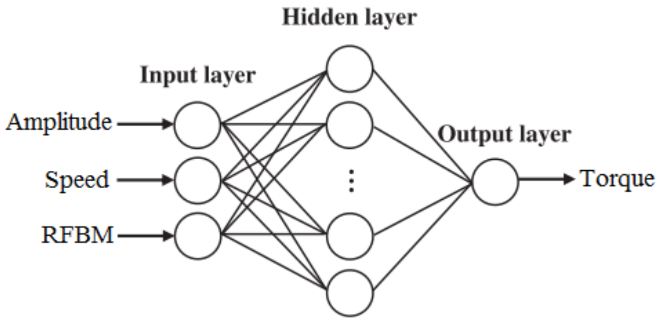


Fig. 3 MLP feed forward ANN

4. Results and discussion

4.1 Regression analysis

A best subsets approach is used to scrutinizing all possible models using listed set of terms. In this approach in the beginning all models which have only one term involved are checked and the two best models based on a higher coefficient of determination (R2) value are presented. Then same route is used to check the all models in which two terms involved. This process continues until all terms have been taken into account. The end result is nineteen models with 1–10 terms and their summary of statistics. The statistics that Minitab provides to choose a better model is shown in Table 3. Fig. 4a-d illustrates the trend of coefficient of determination (R2), adjusted coefficient of determination (R □2), Mallows' statistic (Cp) and standard error (S) with a number of terms (P). It is observed that the after fifth terms every model have higher values of R2 and R □2 and the after sixth term lower in Cp and S . In the statistics higher value of R 2 and R □2 is better, when comparing the models with the same and different number of terms respectively. Therefore, the model number fifteen with eight numbers of terms is best based on R 2 and R □2 criteria's. Similarly, model fifteen is showing minimum values of Cp and S, see Fig 4c-d. The smaller and closer to number of term value of Cp shows the model is better in predication and smaller S is pointed toward the lower variability about the regression line.

From the subset analysis (Table 3), the final third-order general regression model for tapping torque obtained is as follows:

$$Torque = 553.148 - 10.5433 * T_s - 48.0338 * \Phi - 1.48419 * A^2 + 0.071195 * {T_s}^2 + 2.83728 * A * \Phi + 0.232474 * T_s * \Phi - 0.016352 * A * T_s * \Phi + 0.103566 * A^3 \quad (2)$$

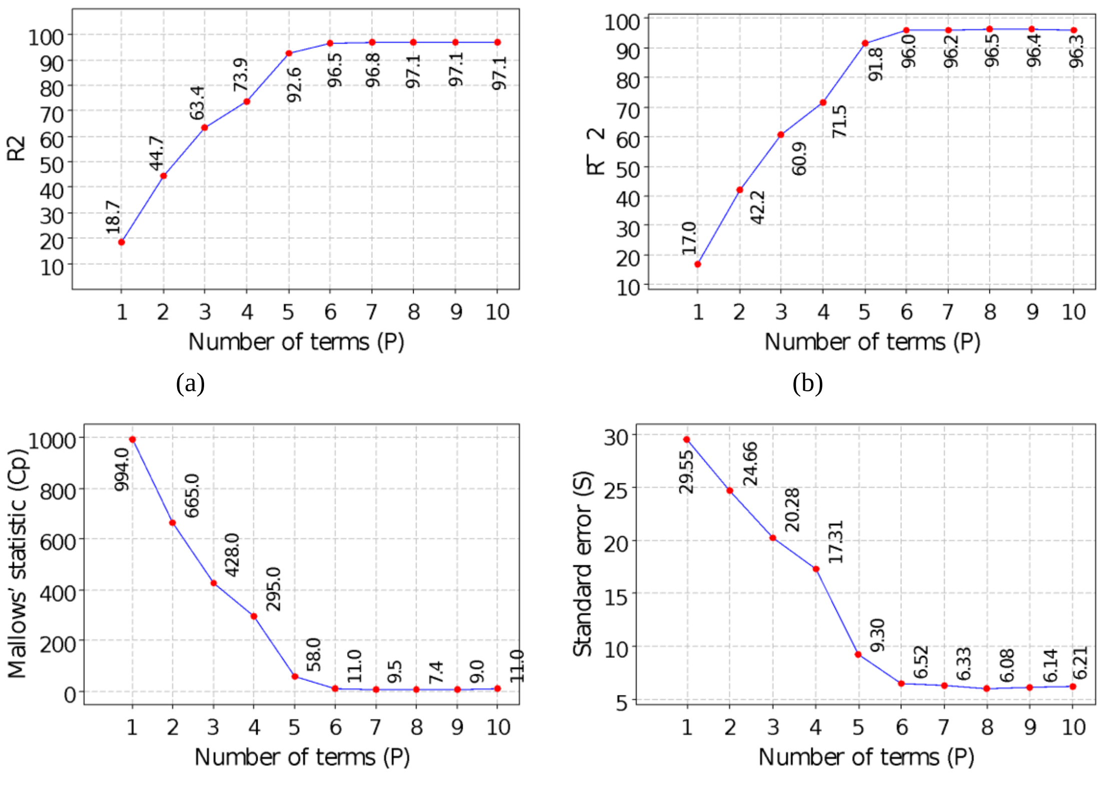
The above equation is third-order polynomial regression equation representing the torque as a function of vibration assisted tapping factors such as vibration amplitude (A), tapping speed (Ts) and a ratio of forward-backward movement (Φ) with their interaction and higher order terms.

The t-test is used to examine the significance of the individual term involved in the model at the 95% confidence level. The output from MINITAB 16 (coefficient, SE coefficient, t-value and t-significance) associated with individual term are presented in Table 4. If the t-significance value associated with individual term are less than 0.05, then those terms statistically significant to the models. The t-significance value of all terms of regression model (equation number) presented in Table 4 are less than 0.05, it is concluded that every term plays important role in the equation. The degrees of freedom (DF), mean square (MS) and F-value and F-Significant (ANOVA) associated with regression model are presented in Table 5. Since the F-Significant in Table 5 is less than 0.05, there is a statistically significant relationship between tapping torque and the forecaster variables at the 95% confidence level. Similarly, ANOVA results of the individual term as it were involved in the model summarized in Table 6. The F-Significant of individual term in Table 6 is less than 0.05. Therefore, all terms included in the model are statistically significant at the 95% confidence level. Thus, the developed model is satisfactorily reliable.

Table 3 – Subsets Analysis

Sr. No	A	T_s	Φ	A^2	$T_s{}^2$	$A*T_s$	$A*\Phi$	$\Phi*T_s$	$A*T_s*\Phi$	A^3	P	R2	$\bar{R}$2	Cp	S
01			×								1	18.7	17	994	29.55
02								×			1	12.6	10.7	1072	30.64
03		×			×						2	44.7	42.2	665	24.66
04				×						×	2	29.3	26.1	862	27.88
05		×	×		×						3	63.4	60.9	428	20.28
06		×			×			×			3	61.0	58.3	459	20.94
07		×		×	×					×	4	73.9	71.5	295	17.31
08	×	×			×					×	4	72.3	69.7	315	17.84
09		×	×	×	×					×	5	92.6	91.8	58	9.30
10	×	×	×		×					×	5	91.0	90	78.5	10.26
11		×	×	×	×		×			×	6	96.5	96	11	6.52
12		×	×	×	×				×	×	6	95.6	94.9	22.8	7.32
13		×	×	×	×		×	×		×	7	96.8	96.2	9.5	6.33
14		×	×	×	×	×	×			×	7	96.5	95.9	12.2	6.53
15		×	×	×	×		×	×	×	×	8	97.1*	96.5*	7.4*	6.08*
16		×	×	×	×	×	×	×		×	8	96.8	96.2	10.7	6.35
17		×	×	×	×	×	×	×	×	×	9	97.1*	96.4	9	6.14
18	×	×	×	×	×		×	×	×	×	9	97.1*	96.4	9.3	6.16
19	×	×	×	×	×	×	×	×	×	×	10	97.1*	96.3	11	6.21

P- Number of terms, R2-Coefficient of determination, $\bar{R}$2-Adjusted coefficient of determination, Cp -Mallows' statistic and S-Standard error. * Indicates most significant value



(a) (b) (c) (d)

Fig. 4a-d Statistics with number of terms; (a) coefficient of determination, (b) Adjusted coefficient of determination, (c) Mallows' statistic and, (d) standard error

Table 4 – Summary statistics for individual term

Terms	Coefficient	SE Coefficient	t-value	t-significance
Constant	553.148	16.3378	33.8569	0.000
$\boldsymbol{T_s}$	-10.543	0.4514	-23.3590	0.000
$\boldsymbol{\Phi}$	-48.034	6.4978	-7.3924	0.000
A^2	-1.484	0.0792	-18.7469	0.000
$\boldsymbol{T_s}^2$	0.071	0.0030	23.8784	0.000
$A*\boldsymbol{\Phi}$	2.837	0.6300	4.5033	0.000
$\boldsymbol{\Phi} *\boldsymbol{T_s}$	0.232	0.0822	2.8287	0.007
$A*\boldsymbol{T_s}* \boldsymbol{\Phi}$	-0.016	0.0078	-2.0844	0.044
A^3	0.104	0.0052	19.8782	0.000

Table 5 – ANOVA table for model fitting

Source	d.f	Sum of squares	Mean squares	F-Value	F-Significant
Model	8	4798.5	5998.3	161.938	0.000
Residual	39	1444.6	37		
Total (corrected)	47	49431.0			

Table 6 – ANOVA table for regression coefficients

Source	d.f	Sum of squares	Mean squares	F-Value	F-Significant
$\boldsymbol{T_s}$	1	953.8	20210.9	545.641	0.000
$\boldsymbol{\Phi}$	1	9257.4	2024.2	54.647	0.000
A^2	1	1591.9	13017.8	351.446	0.000
$\boldsymbol{T_s}^2$	1	21119.7	21119.7	570.176	0.000
$A*\boldsymbol{\Phi}$	1	130.6	751.2	20.280	0.000
$\boldsymbol{\Phi} *\boldsymbol{T_s}$	1	135.7	296.4	8.001	0.007
$A*\boldsymbol{T_s}* \boldsymbol{\Phi}$	1	160.9	160.9	4.345	0.044
A^3	1	14636.4	14636.4	395.145	0.000
Residual	39	1444.6	37		
Total (corrected)	47	49431.0			

The model adequacy is verified by carrying out a residual analysis. In residual analysis, residual plots are used to examine the goodness-of-fit of the regression model as well as identify any violations of the underlying assumptions (normality, independence, and constant variance of residuals). If these assumptions are gratified, then regression model is adequate and residual is structure -less. In the present model, the residuals are appearing normally distributed (shown in the Fig. 5a-b probability and histogram plots) and generally random (shown in the Fig. 5c-d, which display the residuals against their fitted values and in their observation order). The points in the normal probability plot are shown a general form of straight line and it directs the residuals are normally distributed, see Fig. 5a. If the points on the plot are departing from a straight line, then the normal probability assumption is invalid.

Similarly, the histogram frequency distribution plot is shown data centered at zero directs the residuals are normally distributed, see Fig. 5b. If the pattern is shown long tail on one side, it indicates the skewed distribution, whereas if it is shown the bars far away from each other indicate the outliers. The points in residual versus the fitted values plot have shown a randompattern of residuals on both sides of zero line and it has ensured the constant variance assumption, see Fig 5c. In Fig 4d residual versus the order plot has shown the data according to the observation order and it is helping to find time related effects. A tendency of positive and negative residuals in the plot (Fig 5d) is pointed toward positive correlation. Correspondingly, Durbin–Watson test is used to examine the independence assumption on the residuals. At the 95% confidence level, when the number of variables is three and the number of residuals is forty eight, the upper bound value of Durbin–Watson test is 1.674 [42]. Durbin–Watson test statistic for this model was 2.25, which is greater than the upper bound value. Hence, independence assumption on the residuals was satisfied for this model. The results predicted by regression model are compared with experimental results in Fig 5e. It shows the model prediction presents a good agreement with the experimental data.

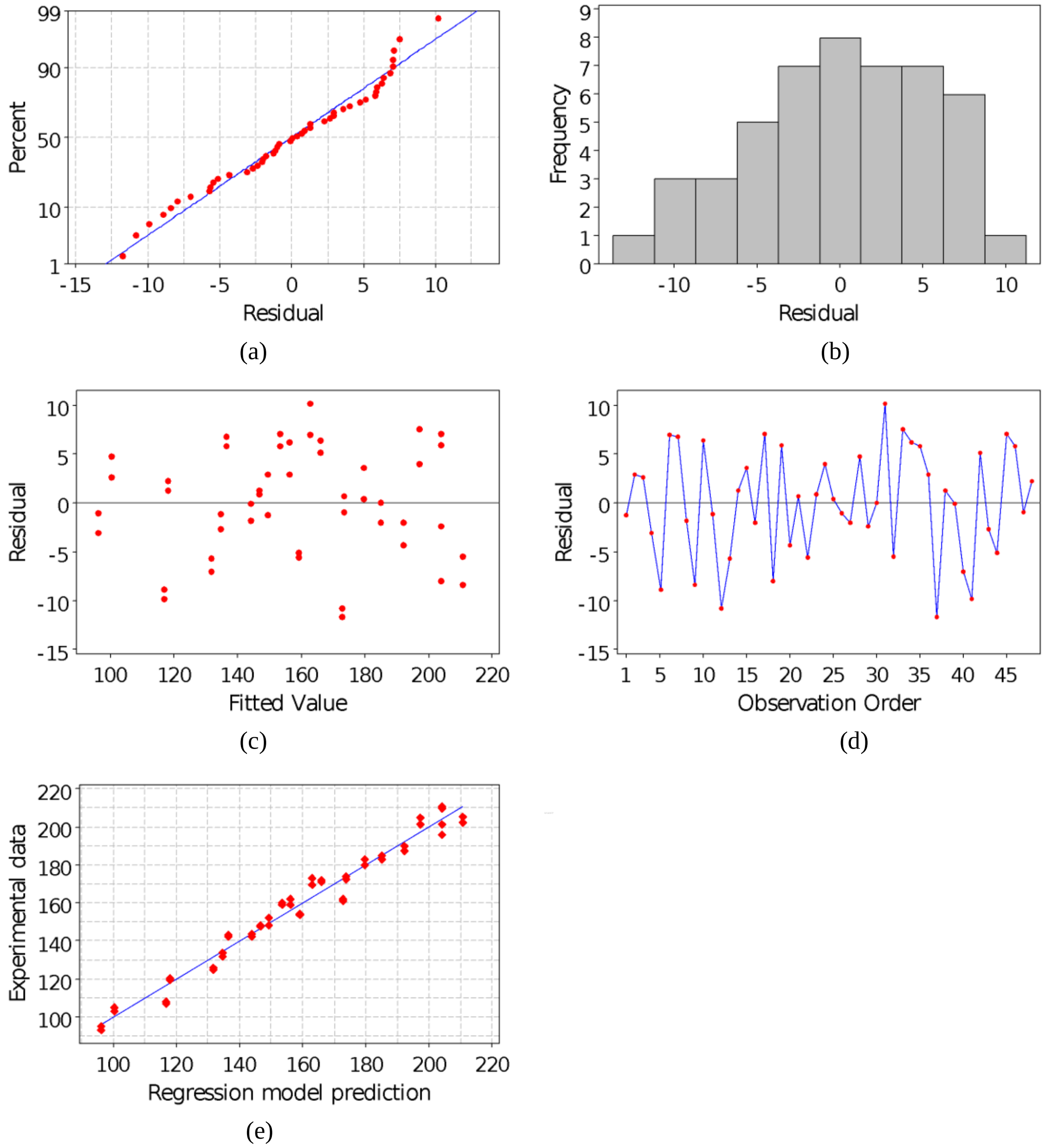


Fig. 5 a-e; (a) Normal probability plot of residuals, (b) Histogram of the residuals, (c) residual versus the fitted values, (d) residual versus the order of the data and, (e) Comparison of regression results with experimental measurements.

4.2 Construction and analysis of ANN

Change in the structural parameter will make a difference in the output predictions. To design a stable network, it would be more appropriate to carry out a parametric study of changing the network parameters and testing the correspondingly changing stability of the ANN. Determining the most appropriate parameter for each problem constitutes a problem itself, and their selection is extremely important.

In this study, a multilayer feed-forward back propagation neural network model was used for the estimation of required tapping torque. The data generated from the systematic DOE is shown in the table 1 and used for ANN modeling. The three independent parameters, namely amplitude, speed and RFBF represent the inputs to ANN model and torque represents the output. Normalization of ANN inputs to a certain range is required in order to make the activation function to identify the inputs at the minimum and maximum range of the data set. Although there are various normalization techniques, their common characteristic is to convert the data sets to desired levels by using a scaling factor. In all of the analysis conducted in the study, each set of inputs and output values is scaled into the [-1, 1] range according to eq. (3).

$$X_N = 2\frac{X - X_{min}}{X_{max} - X_{min}} - 1 \qquad (3)$$

Where X_N is the normalized value of a certain parameter, X is the measured value for this parameter and X_{min} and X_{max} are the minimum and the maximum values in the database for this parameter, respectively.
The MATLAB neural network toolbox was used to train the developed network models. In this part of the study, different ANN models were designed and tested. The successful models are summarized in Fig. 6a-c and 7a-c. For present model construction, 5 different learning algorithms, 4 different transfer functions, 1-3 hidden layers, and all possible combinations of 4-7 neurons at hidden layer are tried with higher number of epochs. The dataset was divided randomly into 3 groups. The groups were as follows: one half – training set, one quarter – validation set and one quarter – test set. The training program was written in such a way that whenever the program ran, the whole dataset was randomly divided into these three groups of sub data.
In the present study, performance of networks was determined on the basis of standard deviation (σ) and the average absolute error (Er). Among these models, the fastest model having the best generalization capability with lower standard deviation and error is selected for prediction of tapping torque. From Fig. 6a-c and 7a-c shows that, Levenberg– Marquardt algorithm having a high error percentage for first four experiments than the Batch Gradient Descent algorithm and Quasi-Newton algorithms. But compared to other algorithms, it is having very low, almost zero standard deviation for 6 or higher number of hidden neurons. Final selected model has one hidden layer with 7 neurons and Levenberg– Marquardt algorithm (LMA) as the learning algorithm. Whereas, it has a tan-sigmoid (tansig) and linear (purelin) transfer function between the layers. However, learning rate was kept at 0.1.

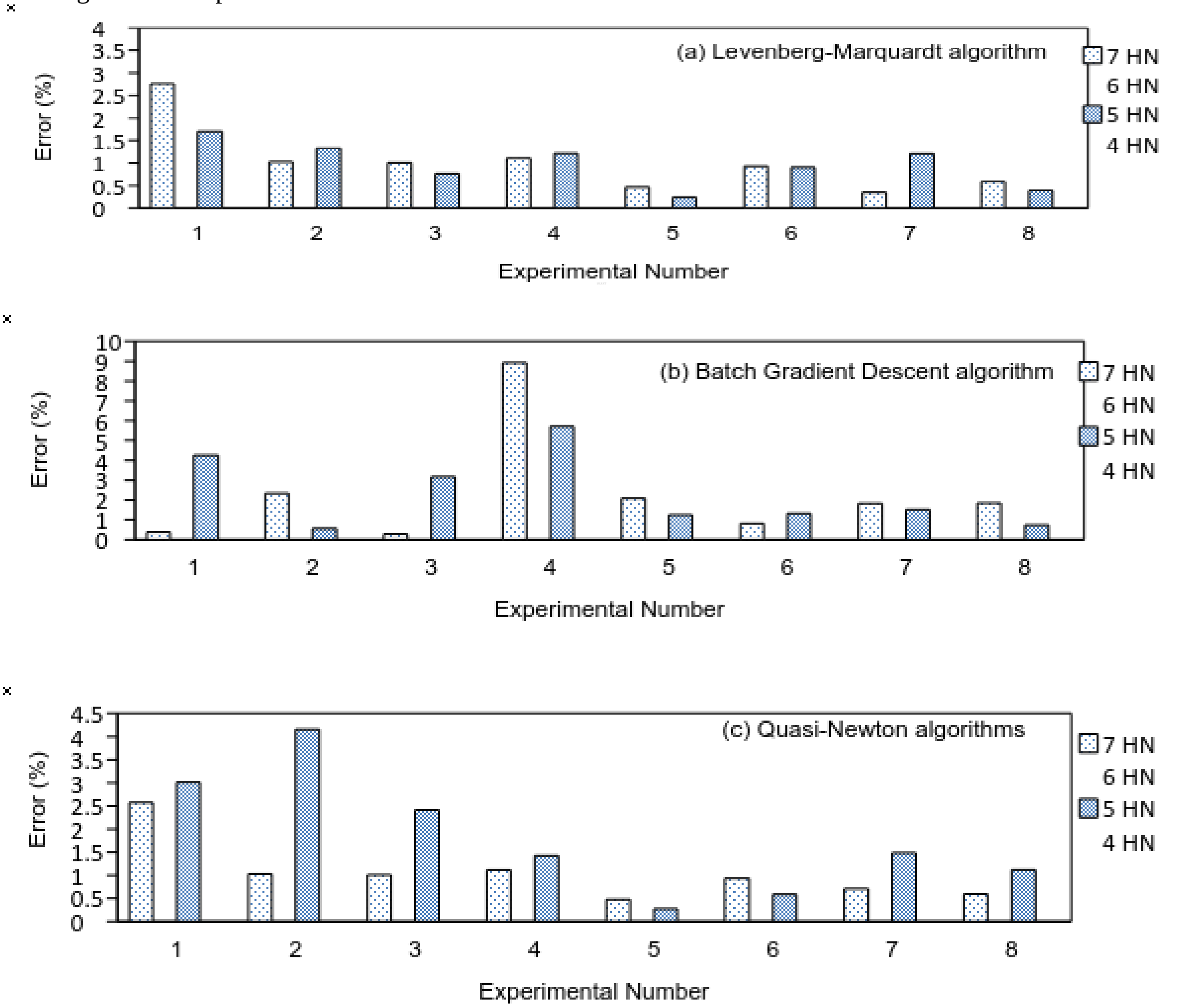


Fig. 6a-c Variation of average absolute error with respect to different number of hidden neurons (a) Levenberg–Marquardt algorithm (b) Batch Gradient Descent algorithm (c) Quasi-Newton algorithms

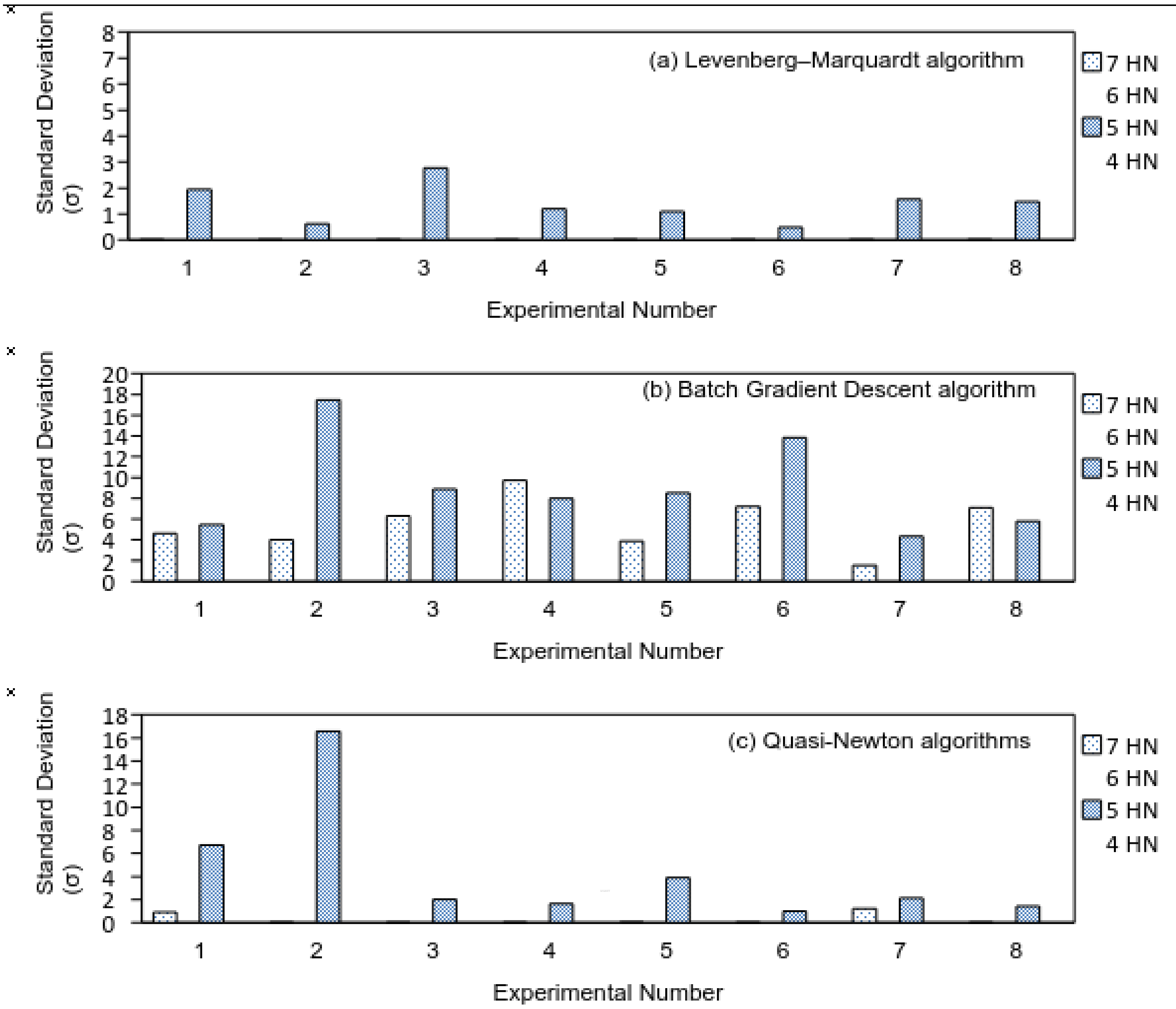


Fig. 7a-c Variation of standard deviation with respect to different number of hidden neurons (a) Levenberg–Marquardt algorithm (b) Batch Gradient Descent algorithm (c) Quasi-Newton algorithms

The constructed model is now used for the prediction of tapping torque and results obtained were compared with the experimental results. The results indicate that the ANN model has been successfully applied to the tapping parameters of Ti6Al4V. The comparison of results is shown in Fig. 8, from the figure it can be seen that ANN predictions closely follows the experimental values. The validation for the tapping torque values using ANN has been listed in Table 1. It is clear from Table 1; the percentage of error between the experimental and predicted values is found that a minimum of 0 and maximum of 2.76. This error is a reasonable one and shows that the ANN model predicted satisfactory the required tapping torque for titanium material.

International Journal of Latest Research in Engineering and Technology (IJLRET)
ISSN: 2454-5031
www.ijlret.com || Volume 02 - Issue 09 || September 2016 || PP. 01-13

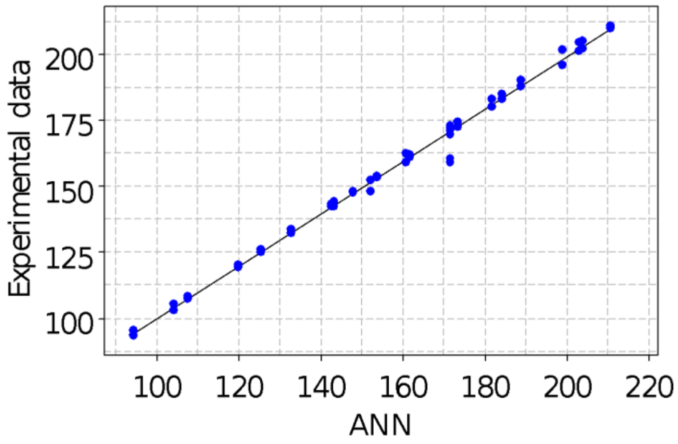


Fig. 8 Experimental data vs. ANN results

4.3 Regression Vs. ANN

In the present study, the same data set is used in order to compare the performance of regression and ANN. First, the regression coefficients are found by forming the third-order general regression model with three independent variables. The finalized model was gauged on the basis of reliability indicators such as standard error (S), coefficient of determination (R2), adjusted coefficient of determination (R2), and Mallows' Cp statistic and further evaluated by t-test, f-test, Durbin-Watson test and residual plots.Second, to create an ANN suitable for the present work and to have a good prediction capability, different network configurations are designed with different learning algorithms and with different structural parameters. Final optimized network structure is discussed in detail in section 4.2.The performance results obtained for both regression and ANN are compared in Fig. 8. An ANN prediction follows more closely to the experimental results than the regression results. Despite the variation of results in regression the accuracy of prediction is near to 99%. However, the error rates of ANN of are less than the regression.

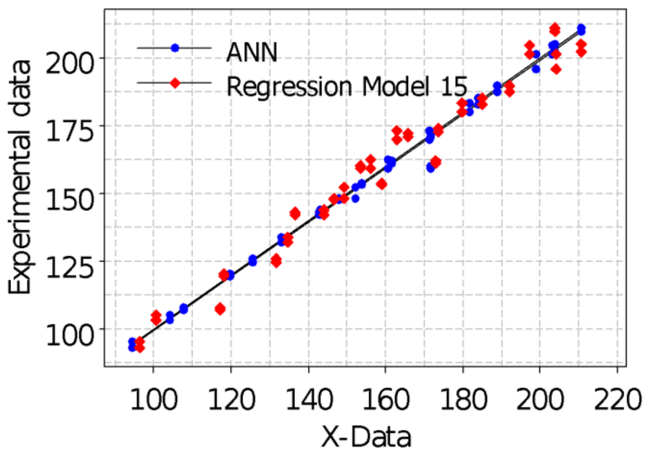


Fig. 9 Regression vs. ANN results

Conclusions

This paper has illustrated performance of tapping process in the presence of controlled vibrations for titanium alloy. To establish the relationship between the controlled vibrations and the maximum torque in tapping process, a regression analysis and ANN systematically carried out based on general full factorial design. The comparisons were made of the above approaches after testing their performance on 10 randomly selected test cases. This paper also discussed the effect of tapping speed and vibration parameters on maximum torque in the tapping process. The key findings of this study as follows:

1. Both the regression and ANN approach were seen to be sufficient for estimating tapping torque with very small test error. However, the maximum prediction error of the regression model was less than 12.9 % and

the average prediction error was less than 5 %. Whereas, with ANN (with the LM algorithm) maximum prediction error was less than 1.4 % and the average prediction error was less than 0.7 %.

2. The obtained results indicated that the regression and ANN are suitable techniques to construct predictive models for prediction of required tapping torque in titanium alloys. Consequently models can be used successfully to avoid the tap breakage.

Acknowledgment

The authors gratefully acknowledge the partial support provided for this work by National Centre for Aerospace Innovation and Research, IIT-Bombay, a Dept. of Science and Technology-Government of India, The Boeing Company and IIT Bombay Collaboration, and Kalyani Center for Technology and Innovation, Bharat Forge Ltd. Pune.

References

[1]. Cao, T. and J.W. Sutherland, *Investigation of thread tapping load characteristics through mechanistics modeling and experimentation.* International Journal of Machine Tools and Manufacture, 2002. **42**(14): p. 1527-1538.

[2]. Liu, T.-I., et al., *Monitoring and diagnosis of the tapping process for product quality and automated manufacturing.* The International Journal of Advanced Manufacturing Technology, 2013. **64**(5-8): p. 1169-1175.

[3]. Zhang, B., F. Yang, and J. Wang, *Fundamental aspects in vibration-assisted tapping.* Journal of materials processing technology, 2003. **132**(1): p. 345-352.

[4]. Kuo, K.-L., *Experimental investigation of ultrasonic vibration-assisted tapping.* Journal of materials processing technology, 2007. **192**: p. 306-311.

[5]. Nogami, T. and K. Nakano, *Physical and Chemical Roles of Metalworking Fluids in a Vibration-Assisted Tapping System.* Journal of Advanced Mechanical Design, Systems, and Manufacturing, 2007. **1**(4): p. 586-594.

[6]. Kuo, K.L. *A Study on Ultrasonic Vibration Assisted Tapping of Titanium*. in *Advanced Materials Research*. 2008. Trans Tech Publ.

[7]. Pawar, S., et al., *An Experimental Analysis of Ultrasonic Vibration Assisted Tapping of Ti-6Al-4V.* 2014, SAE Technical Paper.

[8]. Pawar, S. and S.S. Joshi, *Experimental analysis of axial and torsional vibrations assisted tapping of titanium alloy.* Journal of Manufacturing Processes, 2016. **22**: p. 7-20.

[9]. Yin, B. and R. Han, *Investigation of the torque characteristics in vibration tapping of hardened steel.* International Journal of Machine Tools and Manufacture, 2006. **46**(6): p. 623-630.

[10]. Li, G., et al. *On self-adaptive vibration tapping of titanium alloy*. in *Technology and Innovation Conference, 2006. ITIC 2006. International*. 2006. IET.

[11]. Wang, L., et al. *A Compound Vibratory Mode in High Speed Vibratory Tapping*. in *Advanced Materials Research*. 2009. Trans Tech Publ.

[12]. Lu, H.M., D.Y. Zhang, and Y. Liu. *Research on the Vibration Tapping Performance of Particle Reinforced Aluminum Matrix Composites*. in *Advanced Materials Research*. 2011. Trans Tech Publ.

[13]. Han, F.Q., Z.Z. Li, and D.Y. Zhang. *Study on Oblique Cam Type Mechanical Torsional Vibrator*. in *Applied Mechanics and Materials*. 2012. Trans Tech Publ.

[14]. Yang, L., et al. *Application of Taguchi Method in Vibration Tapping Process*. in *Advanced Materials Research*. 2012. Trans Tech Publ.

[15]. Zhang, D.-y. and D.-C. Chen, *Relief-face friction in vibration tapping.* International journal of mechanical sciences, 1998. **40**(12): p. 1209-1222.

[16]. Kanlayasiri, K. and S. Boonmung, *Effects of wire-EDM machining variables on surface roughness of newly developed DC 53 die steel: Design of experiments and regression model.* Journal of materials processing technology, 2007. **192**: p. 459-464.

[17]. Çaydaş, U. and A. Hasçalık, *A study on surface roughness in abrasive waterjet machining process using artificial neural networks and regression analysis method.* Journal of materials processing technology, 2008. **202**(1): p. 574-582.

[18]. Özel, T. and Y. Karpat, *Predictive modeling of surface roughness and tool wear in hard turning using regression and neural networks.* International Journal of Machine Tools and Manufacture, 2005. **45**(4): p. 467-479.

[19]. Cekic, A. and D. Begic-Hajdarevic, *Definition of Mathematical Models of High-alloyed Steel 1.4828 in CO 2 Laser Cutting.* Procedia Engineering, 2015. **100**: p. 435-444.

[20]. Ramezani, M. and A. Afsari, *Surface roughness and cutting force estimation in the CNC turning using artificial neural networks.* Management Science Letters, 2015. **5**(4): p. 357-362.

[21]. Muthukrishnan, N. and J.P. Davim, *Optimization of machining parameters of Al/SiC-MMC with ANOVA and ANN analysis.* Journal of materials processing technology, 2009. **209**(1): p. 225-232.

[22]. Palanisamy, P., I. Rajendran, and S. Shanmugasundaram, *Prediction of tool wear using regression and ANN models in end-milling operation.* The International Journal of Advanced Manufacturing Technology, 2008. **37**(1-2): p. 29-41.

[23]. Tosun, N. and L. Özler, *A study of tool life in hot machining using artificial neural networks and regression analysis method.* Journal of Materials Processing Technology, 2002. **124**(1): p. 99-104.

[24]. Lin, J., D. Bhattacharyya, and V. Kecman, *Multiple regression and neural networks analyses in composites machining.* Composites Science and Technology, 2003. **63**(3): p. 539-548.

[25]. Korkut, I., A. Acır, and M. Boy, *Application of regression and artificial neural network analysis in modelling of tool–chip interface temperature in machining.* Expert Systems with Applications, 2011. **38**(9): p. 11651-11656.

[26]. Badkar, D.S., K.S. Pandey, and G. Buvanashekaran, *Development of RSM-and ANN-based models to predict and analyze the effects of process parameters of laser-hardened commercially pure titanium on heat input and tensile strength.* The International Journal of Advanced Manufacturing Technology, 2013. **65**(9-12): p. 1319-1338.

[27]. Amamou, R., N.B. Fredj, and F. Fnaiech, *Improved method for grinding force prediction based on neural network.* The International Journal of Advanced Manufacturing Technology, 2008. **39**(7-8): p. 656-668.

[28]. Aydin, G., I. Karakurt, and C. Hamzacebi, *Artificial neural network and regression models for performance prediction of abrasive waterjet in rock cutting.* The International Journal of Advanced Manufacturing Technology, 2014. **75**(9-12): p. 1321-1330.

[29]. Kurt, A., *Modelling of the cutting tool stresses in machining of Inconel 718 using artificial neural networks.* Expert Systems with Applications, 2009. **36**(6): p. 9645-9657.

[30]. Krajewski, S. and J. Nowacki, *Dual-phase steels microstructure and properties consideration based on artificial intelligence techniques.* Archives of Civil and Mechanical Engineering, 2014. **14**(2): p. 278-286.

[31]. Yang, X.-w., et al., *Prediction of mechanical properties of A357 alloy using artificial neural network.* Transactions of Nonferrous Metals Society of China, 2013. **23**(3): p. 788-795.

[32]. Kalogirou, S.A., *Applications of artificial neural-networks for energy systems.* Applied Energy, 2000. **67**(1): p. 17-35.

[33]. Kalogirou, S.A., *Applications of artificial neural networks in energy systems.* Energy Conversion and Management, 1999. **40**(10): p. 1073-1087.

[34]. Zhao, J., et al., *Modelling of the hot deformation behaviour of a titanium alloy using constitutive equations and artificial neural network.* Computational Materials Science, 2014. **92**: p. 47-56.

[35]. Reddy, N., et al., *Modeling medium carbon steels by using artificial neural networks.* Materials Science and Engineering: A, 2009. **508**(1): p. 93-105.

[36]. Powar, A. and P. Date, *Modeling of microstructure and mechanical properties of heat treated components by using Artificial Neural Network.* Materials Science and Engineering: A, 2015. **628**: p. 89-97.

[37]. Malinov, S. and W. Sha, *Application of artificial neural networks for modelling correlations in titanium alloys.* Materials Science and Engineering: A, 2004. **365**(1): p. 202-211.

[38]. Atici, U., *Prediction of the strength of mineral admixture concrete using multivariable regression analysis and an artificial neural network.* Expert Systems with applications, 2011. **38**(8): p. 9609-9618.

[39]. Rawlings, J.O., S.G. Pantula, and D.A. Dickey, *Applied regression analysis: a research tool*. 1998: Springer Science & Business Media.

[40]. Demuth, H., M. Beale, and M. Hagan, *Neural network toolbox™ 6.* User's guide, 2008.

[41]. Kaytez, F., et al., *Forecasting electricity consumption: A comparison of regression analysis, neural networks and least squares support vector machines.* International Journal of Electrical Power & Energy Systems, 2015. **67**: p. 431-438.

[42]. Durbin-Watson, *Durbin-Watson Significance Tables*.