An Intelligent Prediction Model for Thrust Force and Torque Using Machine Learning Approach in Friction Drilling Process

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Abstract

Friction Drilling is a Chip less hole-making process in which a conical tool is used to form the hole on the sheet metal by frictional heating. Metal flows plastically in both upward and downward directions. The extruded metal on top is converted into the boss with the help of the shoulder of the tool while downward extruded material is well controlled to form the bush. A formed bush can be threaded and used to screw other connecting parts. The process is suitable for sheet metal having a thickness of less than 5 mm and finding applications in Automobiles, Furniture, etc. Thrust force and Torque are two Important parameters which affect the frictional heating during hole formation and thereafter tool wear and hole quality. In this work, experimentation on low carbon steel, AISI 1018 has been carried out at the Vertical Machining Center. For real-time Data Acquisition of Thrust Force and Torque, Kistler Dynamometer equipped with DynoWare software is used. The Thrust force and Torque prediction model for friction drilling of AISI 1018 steel has been developed using Random Forest (RF) and Regularization Methods (RM). Ridge and Lasso Regression which are important tools in RM have been utilized to model the measured data for Thrust force and Torque. GridSearch(GS) technique has been used for tuning hyperparameters. The Random Forest (RF) gives a reliable prediction of thrust force with R^2= 0.97, Mean Absolute Error (MAE) = 71.91 N, Root Mean Square Error (RMSE) = 96 N on training data and R^2 = 0.92, MAE =140 N, RMSE = 96 N on test data. Similarly, Torque Prediction Random Forest (RF) gives better predictions than RM on Test Data with R^2 = 0.93, Mean Absolute Error (MAE) = 0.22 Nm, and RMSE = 0.29 Nm but on Training data Performance is almost similar both the methods. Comparisons among RF, Ridge, and Lasso regression show that RF is an effective technique to ensure high predictive accuracy of Thrust Force and Torque.

Keywords
Friction drilling, Random Forest, Machine Learning, Ridge & Lasso Regression.

1. Introduction

Improvement in the product quality at a minimum cost has been primary motive of all the manufacturing industries. Analyzing the quality problems and there after carrying out corrective actions is cumbersome and time-consuming approach. This also hides many quality problems and exaggerates the production cost. Real time data acquisition or online monitoring of manufacturing process is proposed an effective way to analyze the quality problems efficiently. In this work real time investigations have been carried out on Friction Drilling Process. Basically, friction or thermal drilling process is employed for sheet metal appliances of different sections viz. Tubular, Rectangular, I etc. having thickness up to 5 mm. Friction drilling tool which has typical geometry and different sections viz. Center, Conical Cylindrical, Shoulder and shank for holding purpose (Pantawane 2011). In this process high speed rotating tool approaches the workpiece which generates frictional heat (500°-900°) and causes the material to flow plastically (Alphonse et al. 2021). The Extruded material above the workpiece is rounded off as Boss by bottom face of shoulder. The downward extruded material is controlled and made into cylindrical shaped with the cylindrical section of friction drilling tool which forms the bush. The Bush thus formed can be threaded in consecutive thread forming process to make the threaded hole. The length of bush is generally three times the material of thickness and offers good clamping strength (Boopathi et al. 2013). Here Thrust Force and Torque have been measured real time with Kistler 9257B Dynamometer and analyzed. Machine Learning Approach Viz. Random Forest and Regularization method have been applied for intelligent monitoring. Random Forest, Ridge and Lasso regression methods have been applied for prediction. GridSearch(GS) technique has been used for tuning hyperparameter. Data modeling and analysis show that process exhibits good correlation and Prediction.

1.1 Objectives

This study aims to create a Supervised Machine Learning model for Prediction of Thrust Force and Torque produced during Friction drilling operation of AISI 1018 steel and this study is also focus on building an experimental setup for real time monitoring of Thrust force and Torque with the help of Kistler Dynamometer in Friction Drilling operation. This real time data from the Dynamometer we collected on different Speed, feed and T/D ratio values. This work is also included technique like Hyperparameter tuning with the help of GridSearch (GS) for optimization of Hyperparameters of Machine Learning techniques and studied the Effect of Performance of each model.

2. Literature Review

Friction Drilling is the best solution for all sheet metal joining problems like wastage of material, large cycle time and more cost (Pantawane, Ahuja 2011). During this process Thrust force is the axial force generated and this force high initially and goes to minimum at end of process. Torque and Thrust force vary in same trend as variation in speed and feed. We have to select optimum values of Input parameters like Spindle speed, feed rate etc. so that we get optimum values of forces and torque. High value of thrust force deforms sheet metal and reduce tool life (Boopathi et al. 2013). Study on prediction of cutting forces was conducted for Turning of AISI 4340 by using Gaussian Process Regression (GPR) Algorithm and compared the result with Support vector Regressor (SVR) and Artificial neural network (ANN). Model performance evaluated by using R^2 , Mean absolute percentage error (MAPE) and Root mean square error (RMSE). Lowest computational time in terms of the training consumes GPR as compared to other two models around 0.35087 sec studied by (Alajmi, Almeshal 2021). Milling Process is used in this study for measuring three orthogonal components of Cutting forces. Tool wear monitoring study was conducted on the basis of Force measurement by using Kistler Piezoelectric dynamometer in dry milling. This force signal filtered by using amplifier and further used for training the CNN model for prediction of tool wear. Tool wear is very crucial phenomenon and when we want good quality product in terms of Surface Finish for that accurate prediction of tool wear is also important. Measurement of Flank wear did by using digital microscope. For prediction Convolutional Neural Network (CNN) technique were used. Cutting Force signals used for prediction of tool wear and from result we can see that CNN is very good technique for finding out Correlation between Cutting force and flank tool wear (Martínez-Arellano et al. 2018).

During machining temperature of tool-workpiece interface affects largely on tool wear. To understand this problem in better way to works on Tool wear prediction on the basis of Temperature signals. Around 303 data samples used to train the deep learning model and each data sample consist Input parameters, Temperature, Tool wear values. RMSE and Coefficient of determination (R^2) metrics used for evaluation of model. Model used in this study was SSAE-BPNN for tool wear prediction. To confirm the Accuracy and Performance of this model Compare Predictive performance with that of traditional ML Algorithms such as neural network and support vector regression (SVR) (Tielin Shi et al. 2021). In this paper author works on Random Forest algorithm for quality prediction of reamed bores. The data were collected from serial production of high-precision hydraulic valves. Data preparation and feature extraction carried out on Python 3.7 Environment and for data analysis carried with the help of Scikit-learn library. Quality prediction were carried out by prediction of diameter, roundness, straightness and concentricity of reamed holes (Schorr et al. 2020). Study on Tool wear prediction in Drilling operation is carried out with the help of hybrid machine learning approach. This approach based on optimizing the extreme gradient boosting algorithm. Spiral dynamic optimization (XGBoost-SDA) is used for choosing hyperparameters. Copper and cast-iron these two-workpiece used for creating dataset. Prediction results were compared with Artificial neural Network (ANN) and support vector machine (SVM). XGBoost-SDA gives better results as compared to other algorithm and it's measured by various metrics such as MAE, RMSE and R^2 (Alajmi, Almeshal 2020). This study was conducted for Prediction and Optimization of surface roughness and flank wear of aluminium alloy during high-speed milling. Four Input parameters were selected and three levels of each for Design of Experiments. Support Vector Regression (SVR), Gradient boosting tree (GBR) and Artificial Neural Network (ANN) were used for prediction of surface roughness and maximum flank wear. Several quality metrics were used to check performance of model such as RMSE, MAE and R^2 (Anh-Tu Nguyen et al. 2022).

3. Methods

3.1 Experimental Setup

The Experiments have been carried out on 3-axis CNC Vertical Machining Center PVM 40 which has variable speed up to 5000 RPM. The workpiece material used in this study is AISI 1018, which is low carbon steel and mainly used for fabrication work. The circular pipe having 32 mm outer diameter and 300 mm length have been used for drilling the holes. M10(Φ 9.2 mm) Tool of Tungsten Carbide in Cobalt matrics is used for making the holes on the workpiece. AISI 1018 Circular pipe is fixed on Fixture which in turn mounted on Kistler Dynamometer 9257B. Tool is held in the specially prepared adaptor having Aluminium cooling ring for faster dissipation of heat. Circular pipes of AISI 1018 of three different thickness (1mm, 2mm and 3 mm) have been used to obtained Tool to Diameter ratios (T/D) ratios of 0.11, 0.22 and 0.33 respectively. Machine Parameters Speed (1500,2000,2500 RPM) and Feed (50,75,100 mm/min) have been selected from the literature and screening experiments. Input parameters and range is given in Table 1 and Experimental results are given in Table 2. Figure 1 shows Experimental setup for Friction Drilling Process with Dynamometer and Friction drilled holes is shown in Figure 2.

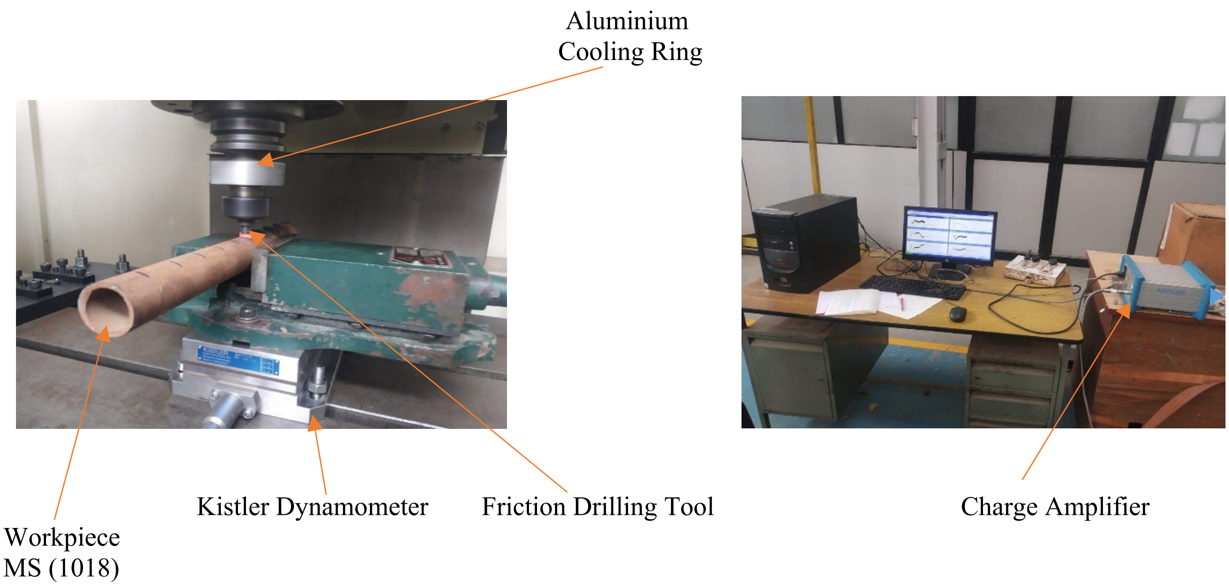

Figure 1. Experimental setup for Friction Drilling

Figure 2. Friction drill Holes

Table 1. Ranges for Input Parameters

Parameters	Range
Spindle Speed (rpm)	1500,2000,2500
Feed Rate (mm/min)	50,75,100
Thickness/Diameter Ratio	0.11,0.22,0.33

Table 2. Experimental Results

Exp No	T/D Ratio	Speed (rpm)	Feed (mm/min)	Torque (Nm)	Actual Thrust Force (N)
1	0.11	1500	50	6.14	796.2
2	0.11	1500	75	6.41	1250.63
3	0.11	1500	100	7.01	1587
4	0.11	2000	50	5.13	748
5	0.11	2000	75	5.42	941
6	0.11	2000	100	5.7	1413.35
7	0.11	2500	50	5.35	732.67
8	0.11	2500	75	4.83	890
9	0.11	2500	100	5.73	1290.5
10	0.22	1500	50	7.05	2006
11	0.22	1500	75	7.6	2327
12	0.22	1500	100	8.74	2574.67
13	0.22	2000	50	6.15	1913
14	0.22	2000	75	6.22	2267.5
15	0.22	2000	100	6.87	2418.2
16	0.22	2500	50	5.03	1807
17	0.22	2500	75	6.07	2132.6
18	0.22	2500	100	5.96	2389.5
19	0.33	1500	50	8.62	2362
20	0.33	1500	75	9.6	2557.5
21	0.33	1500	100	10.52	2875
22	0.33	2000	50	7.05	2307
23	0.33	2000	75	7.77	2493.6
24	0.33	2000	100	8.8	2710
25	0.33	2500	50	6.08	2269
26	0.33	2500	75	6.88	2322.6
27	0.33	2500	100	6.84	2618

3.2 Random Forest:

Random Forest (RF) is supervised learning technique which is used for solving Regression as well as Classification kind of problems. This technique falls under category of Bagging or bootstrap aggregation of Ensemble Learning. RF is combination of multiple decision trees (DT), where each decision tress is trained on randomly selected samples or bootstrap aggregation of the original dataset. The collection of DT models is used for making prediction of output variable rather than use individual or single model.

With the help of bagging approach RF create subset of data from the original dataset with replacement and each subset of data d_i of sample size S is used for create decision tree t_i from original data D. d_i is considered as a bootstrap sample. Bagging helps to make our model with low bias & low variance and also reduce overfitting (Schorr et al. 2020).

For each subset of sample S one Decision tree t_i is created. At each node, it randomly takes m features out of the M total features and select the best split among those features this is also called “feature bagging”. This split is done on one of the m features or variables that minimize the mean squared error (MSE).

Dataset D = $\{(x_p, y_p)$, p = (1, 2,…,P)$\}$, where x_p and y_p is the input and output data respectively. The number of decision trees or base models T are chosen by the user with the help of n_estimators hyperparameter.

Splitting of node or length of each decision tree t_i it depends on which Hyperparameter’s which we have taken into account. Above procedure repeat for every decision tree and each decision tree gives new predicted value on the basis of each subset of data d_i or Input data (Figure 3).

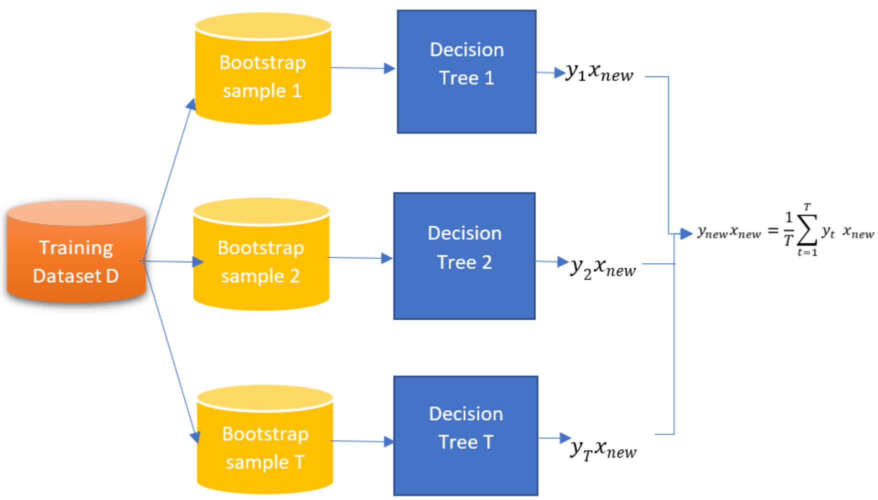

Figure 3. Flow of Random Forest for Regression Problem

3.3 Regularization

Before discussing about Regularization, we just recall normal Linear Regression

$$Y = \beta_0 + \beta_1 \; x_1 \ldots\ldots + \beta_n x_n$$

In Linear Regression our objective is to minimizes the residual sum of squares (RSS)

$$RSS = \sum_{i=1}^{n} \; (y_i - \beta_0 + \sum_{j=1}^{p} \beta_j \, x_{ij}))^2$$

Where,
n = Total Number of Observations
p = total number of features
y_i = Actual output value
β_j = Coefficient of each feature
x_{ij} is the i^{th} observation j^{th} feature value
Generally Linear Regression model is based on least square estimation while finding out optimal fit sometimes least square do not perform well on unseen data. To overcome this problem Regularization comes into picture. Regularization is useful when our model is to complex means low bias and high variance. In this technique our algorithm makes our model with optimum bias-variance values which is also called bias-variance tradeoff. In Regularization there are three methods Ridge, Lasso and Elastic net regression. Ridge and Lasso regression we discussed in next section.

3.3.1 Ridge Regression

In this regression technique we add penalty term (α) and this penalty term is equal to square of coefficient. This technique mainly focused on to find out appropriate small value of penalty term (α) (Bhattacharya et al. 2021). Ridge regression is also called L2 regularization. The objective or loss function for ridge regression is given by

$$\mathrm{RSS} + \alpha \sum_{j=1}^{p} \beta_j^2$$

Ridge regression minimize or shrinks the coefficient towards zero but never reach to zero.

3.3.2 Lasso Regression

Conventional Regression model usually suffers from problem like overfitting and overestimation. When our model contains statistical insignificant terms then overfitting occurs (Bhattacharya et al. 2021). In this regression technique we add penalty term (α) to cost function and this penalty term is equal to absolute sum of coefficient. Lasso stands for Least absolute shrinkage and selection operator and also called L1 regularization. The objective or loss function for ridge regression is given by

$$\mathrm{RSS} + \alpha\sum_{j=1}^{p}|\beta_j|$$

Where α is penalty term or tuning parameter and as we increase the value of α coefficients shrinks towards to zero.

Figure 4 shows Flowchart of Methodology of this Study. This Diagram basically shows working cycle of Machine Learning algorithm from Data collection to the Final Prediction.

Figure 4. Flowchart of the study methodology

4. Data Collection

In this work we measure the Thrust force and Torque with the help of Kistler Dynamometer. Dynamometer is connected with Computer system through charge amplifier. For each experiment we get graphs for thrust force and Torque on DynoWare Software which is installed in system. Data for each drill hole we can take maximum values of Force as well as Torque from the graphs. Collected data was scaled with Min-Max Normalization which is generally used for re-scaled the features before training the Machine learning algorithm.

5. Results and Discussion

The all three-machine learning algorithm was executed in Python Programming language on Google Collab Environment. We use Scikit-learn Library for executing all algorithms and use libraries like Pandas and Matplotlib for Data analysis and Data Visualization respectively. With help of Scikit-learn library we split our data 80% in training and 20% for test or validation (Anh-Tu Nguyen et al. 2022).

In this study we performed 27 drilling operation at different combination of T/D ratio, spindle speed and feed rate from this we monitor real time Thrust force (N) and torque (Nm) for each hole by using Kistler Dynamometer. From experimental result we visualize relationship between all parameters with thrust force with the help of scatter plot in Python. There is moderate linear relationship between Torque and T/D ratio with Thrust force, but we see Nonlinear relationship with speed and feed rate with Thrust force.

5.1 Hyperparameter tuning for Machine Learning Model

Optimization of any Machine Learning Model is an always challenge to obtained a good solution. Hyperparameter tuning is done to find the best parameters that gives the best performance on validation or Test dataset. Hyperparameter also impacts on control the learning process as well as predictive performance of the model. Moreover, specific selection of hyperparameters useful to avoid overfitting and underfitting of machine learning model. With the help of Hyperparameter tuning we basically trying to minimize the cost function We use traditional technique for hyperparameter tuning which is GridSearch (GS). GridSearch helps to find the optimal hyperparameter from sets of hyperparameter values (Anh-Tu Nguyen et al. 2022). Table 3 represents sets of hyperparameters which we used Random Forest, Ridge and Lasso regression.

Table 3. Hyperparameters for machine learning model

Model	Hyperparameters Tuned	Grid Space	Results
RF	max_depth max_features n_estimators	[3,5,10,15,20] [1,2,3,4] [2,5,10,50,100]	5 2 10
Ridge	Tuning parameter/ Penalty term	[0.01,0.1,0.5]	0.1
Lasso	Tuning parameter/ Penalty term	[0.5,1,5]	1

5.2 Numerical Results

A comparison of predicted value of Thrust force and Torque from Random Forest, Ridge and Lasso regression with experimental values of AISI 1018 workpiece. Table 4 represents results on Training data and Table 5 represents results on Test data. The predicted results shows that the Random Forest (RF) predict Thrust force and Torque value very close to actual values as compared to Regularization Techniques like Ridge and Lasso Regression. RF is collection of multiple decision trees; it has characteristics of automatic feature selection and works on randomly selected dataset these are the same reasons RF gives better results as compared to other techniques.

Table 4. Comparison results of Thrust force (N) and Torque for
on Train Data

Exp No	Experimental Data		Random Forest		Ridge regression		Lasso Regression	
	Thrust Force	Torque	Thrust Force	Torque	Thrust Force	Torque	Thrust Force	Torque
2	1250.63	6.41	1282.29	6.24	1386.6	6.82	1389.21	6.82
3	1587	7.01	1687.14	7.22	1654.06	7.30	1669.53	7.31
5	941	5.42	991.12	5.32	1271.54	5.78	1268.62	5.88
7	732.67	5.35	916.71	5.47	847.95	4.23	740.31	4.21
8	890	4.83	886.34	5.32	1137.4	4.72	1088.83	4.78
9	1290.5	5.73	1290.8	5.72	1394.39	5.20	1336.68	5.22
10	2006	7.05	2158.2	6.85	1803.08	7.38	1816.1	7.26

11	2327	7.60	2214.13	7.58	2064.84	7.86	2078.76	7.75
13	1913	6.15	1860.33	5.56	1685.16	6.33	1686.64	6.19
14	2267.5	6.22	2194.51	6.67	1962.2	6.81	1996.66	6.59
15	2418.2	6.87	2366.24	6.96	2220.78	7.31	2249.45	7.23
16	1807	5.03	1800.97	5.56	1574.24	5.27	1578.88	5.12
17	2132.6	6.07	2013.04	6.14	1821.81	5.76	1797.53	5.60
18	2389.5	5.96	2274.03	6.49	2103.17	6.25	2120.9	6.12
19	2362	8.62	2354.77	8.31	2469.23	8.46	2468.16	8.57
22	2307	7.05	2316.87	7.37	2372.17	7.40	2404.81	7.47
23	2493.6	7.77	2447.88	7.82	2641.03	7.89	2688.06	7.95
24	2710	8.80	2638.82	8.77	2875.47	8.38	2865.97	8.48
25	2269	6.08	2574.92	6.70	2256.94	6.35	2282.25	6.37
26	2322.6	6.88	2426.34	7.02	2510.75	6.84	2520.23	6.93
27	2618	6.84	2571.82	7.85	2791.28	7.33	2841.11	7.49

Table 5. Comparison results of Thrust force (N) and Torque for
on Test Data

Exp No	Experimental Data		Random Forest		Ridge regression		Lasso Regression	
	Thrust Force	**Torque**	**Thrust Force**	**Torque**	**Thrust Force**	**Thrust Force**	**Torque**	**Thrust Force**
1	796.2	6.14	1132.39	6	1115.93	6.34	1098.92	6.42
4	748	5.13	771.3	5.47	997.02	5.28	966.4	5.33
6	1413.35	5.70	1309.48	6.03	1541.9	6.26	1557.92	6.28
12	2574.67	8.74	2458.82	8.73	2307.83	8.36	2283.19	8.27
20	2557.5	9.60	2516.17	9.33	2717.31	8.95	2688.38	9.12
21	2875	10.52	2774.6	10.33	2996.57	9.44	3005.31	9.60

5.3 Graphical Results

Figure (5), (6) & (7) shows the graphical representation of predicted values of Thrust Force from different algorithms in comparison with Experimental results. As we see in Figure (a) Random Forest (RF) gives very close prediction results as compared to Regularization techniques. The reason behind that Random Forest works on Ensemble technique of Machine Learning, where every single decision tree is trained on randomly selected sample data also called as "Bootstrap aggregation" proposed by Schorr et al. 2020. Figure (8), (9) and (10) shows the graphical representation of predicted values of Torque in comparison with Experimental results.

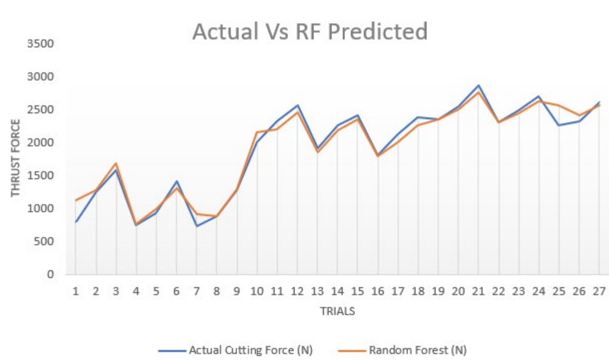

Figure 5. Thrust force

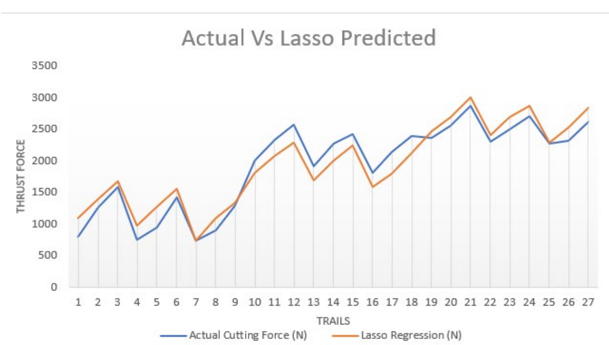

Figure 6. Thrust force

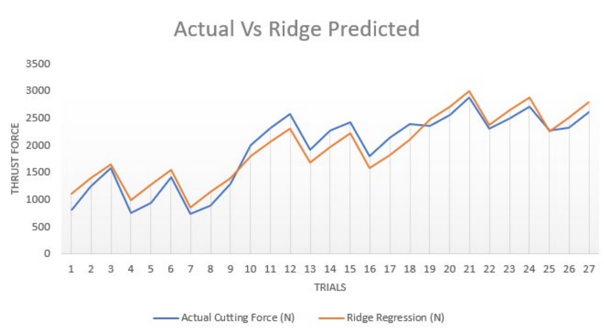

Figure 7. Thrust force

Figure: (5), (6) & (7) Graphical representation of Thrust Force Predicted values in comparison to the Actual measured values

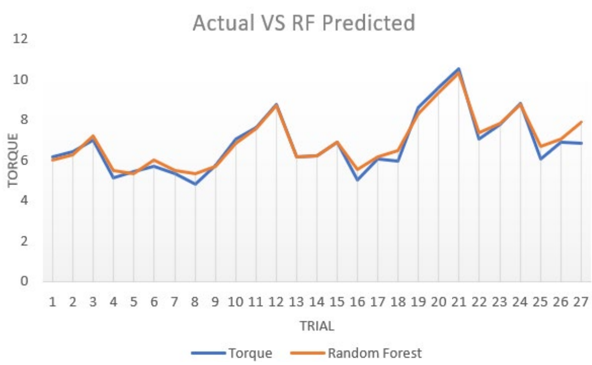

Figure 8.Torque values

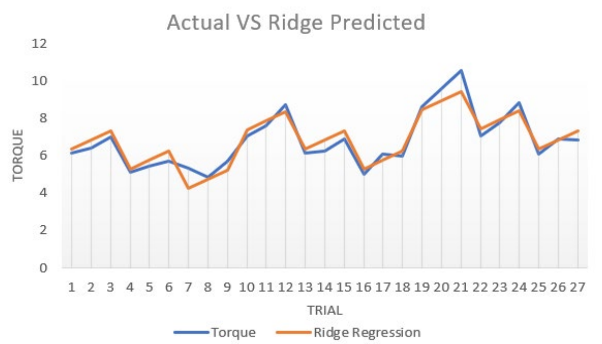

Figure 9. Torque values

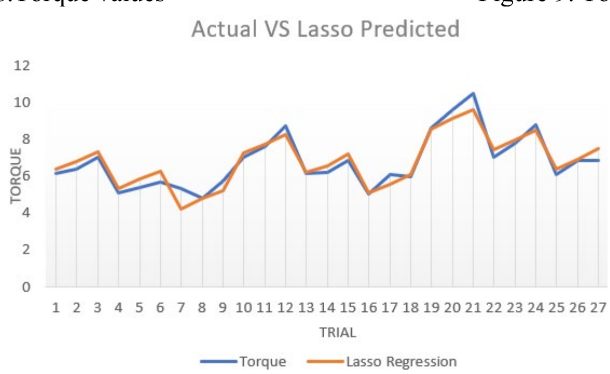

Figure 10. Graphical representation of Torque Predicted values in comparison to the Actual measured values

Figure: (8), (9) & (10) represents graphical representation of Torque Predicted values in comparison to the Actual measured values

5.4 Validation

Table 6 represent the statistical performance indicators for each algorithm in terms of Mean squared error (MSE), Root mean squared error (RMSE) and coefficient of determination (R^2) for thrust force prediction. We calculate all three indicators in newton for each algorithm on both train and test datasets. Table represents values of each performance metrics for each algorithm. As we discussed Random Forest (RF) gives very close results and value of

R^2 in case of RF is around 0.97 on training dataset and 0.92 on test dataset. MAE and RMSE values in case of Random Forest for training data is 71.91 N and 96 N and for test dataset values are 140 N and 171.26 N respectively. In case of Ridge and Lasso Regression value of R^2 is 0.93 and 0.92 respectively on training data. On test dataset R^2 value for both techniques are around 0.91 and 0.88 respectively.

Table 6. Performance of Machine Learning Model for Thrust Force prediction on train and test data

Model	**Training data**			**Test Data**		
	$\boldsymbol{R^2}$	**MAE(N)**	**RMSE(N)**	$\boldsymbol{R^2}$	**MAE(N)**	**RMSE(N)**
Random Forest	0.97	71.91	96	0.92	140	171.26
Ridge Regression	0.93	180.98	203.59	0.91	204.73	249.67
Lasso Regression	0.92	175.86	198.67	0.88	219.29	245.59

Similarly, Table 7 shows statistical performance of all three models in terms of Mean squared error (MSE), Root mean squared error (RMSE) and coefficient of determination (R^2) for Torque prediction. In Torque prediction also Random Forest performs better than Regularization methods. RF gives R^2 value around 0.94 on training data and 0.93 on Test data. MAE and RMSE values in case of Random Forest for training data is 0.28 Nm and 0.37 Nm and for test dataset values are 0.22 Nm and 0.29 Nm respectively.

Table 7. Performance of Machine Learning Model for Torque prediction on train and test data

Model	**Training data**			**Test Data**		
	$\boldsymbol{R^2}$	**MAE(Nm)**	**RMSE(Nm)**	$\boldsymbol{R^2}$	**MAE(Nm)**	**RMSE(Nm)**
Random Forest	0.94	0.28	0.37	0.93	0.22	0.29
Ridge Regression	0.91	0.28	0.34	0.87	0.41	0.48
Lasso Regression	0.94	0.25	0.28	0.89	0.38	0.47

7. Conclusion

The Modeling and prediction of response parameters of any machining process positively impact production in terms of reduction in cost and resources.

1. The result clearly shows that Random Forest algorithm performed much better than Regularization method and it gives MAE between Actual and predicted Thrust Force 140 N on test data.
2. Both regularization techniques Ridge and Lasso Regression gives nearly same prediction in terms of R^2 which is 0.91 and 0.88 on test data respectively.
3. Random Forest gives better results in case of Torque Prediction and both the Regularization techniques gives nearly same results in case of Thrust force and Torque Predictions.
4. For dealing with Underfitting and Overfitting hyperparameters of all three models were tuned with the help of GridSearch (GS) technique from that we get optimum values of Hyperparameters. In case of RF max_depth = 5, max_features =2 and n_estimators =10 these are the optimum values of hyperparameters. Optimum values of hyperparameter in case of Ridge and Lasso Regression are α = 0.1 and α = 1 respectively.

The result shows that the RF could be utilized by process operators to predict thrust force parameters prior to the actual production process in order to save the cost of material and resources.

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