Prediction of cutting forces in MQL turning of AISI 304 Steel using machine learning algorithm

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ABSTRACT

Cutting force play a significant role in enhancing the machining performance as it affects the cutting tool life, surface finish generated and also the energy consumed in obtaining the final product. The machining cost is reduced considerably by effectively minimizing the cutting forces. Minimum quantity lubrication (MQL) is a technique by which cutting fluid is employed in the machining zone in the form of mist, thereby reducing the wastage of cutting fluid and improving the machinability of the process. In this paper, AISI 304 steel is machined using carbide tool in alumina nanoparticle enriched lubrication environment. The calculation of average cutting force is done by varying the input parameters namely cutting speed, feed rate, depth of cut and nanoparticle concentration respectively. The design of experiment is made using response surface methodology (RSM) and further analysis of variance is performed. Furthermore three machine learning based models namely linear regression (LR), random forest (RF) and support vector machine (SVM) are used for predicting the cutting force and comparing the experimental value with that of the predicted value. For accessing the performance of the predicted values, three different error metrics were used namely, coefficient of determination (R^2), mean absolute percentage error (MAPE) and mean square error (MSE) respectively. The predicted values obtained by linear regression model for cutting forces are more accurate as compared to other models.

Keywords: Force; Modelling; Turning; Steel; Nanofluids; Lubrication.

INTRODUCTION

In the present global competitive market, sustainable manufacturing is the need of hour which aims to reduce the resources for utilization without hampering the quality of the finished product. By incorporating sustainable practices in metal cutting industries, the aim is to achieve ecological benefits by posing less threat to the environment (Kopac 2009). Almost in all metal cutting, cutting fluids are employed for facilitating cooling and lubrication along with ease in cutting chip removal. Generally these metal working fluids are toxic in nature and non-biodegradable causing breathing issue along with skin infections in humans. Proper and safe handling of these cutting fluids is to be ensured while machining and during its disposal as it may pollute the soil and water resources. The handling, maintenance and disposal of cutting fluid contributes to 16% of the manufacturing cost (Kulatunga et al. 2015). Therefore in order to minimize this cost there rises a need to find an alternative in form of dry cutting or under such environment having near dry cutting. Minimum quantity lubrication (MQL) is an emerging technique which discharges cutting fluid in the form of pressurized mist in the machining zone thus reducing the bulk usage of cutting fluid and minimizes environmental burden and machining cost (Dubey, Kumar Sharma, and Kumar Singh 2020). The use of different vegetable oil namely canola oil, soybean oil and coconut oil is investigated under MQL condition for turning AISI 4340 steel. The canola oil outperformed among other vegetable oil as it possesses high density and heat transfer coefficient and aided in better tool life (Gunjal and Patil 2018). The advent of nanoparticle enriched cutting fluid methodology has attracted many researchers to machine different materials owing to its advantages in superior surface finish and reduced cutting force, when compared to traditional cutting fluid.

Nanofluids also possesses enhanced tribological properties in terms of coefficient of friction and lubrication performances while machining (Pandey et al. 2019). The performance of turning process is investigated by several researchers by emphasizing the nanofluids MQL lubrication strategy. In one article the effect of carbon nanotube in base oil while turning on AISI D2 steel using carbide insert was studied. The nanofluids assisted machining resulted in reduced cutting force and cutting zone temperature in comparison to conventional lubrication(Sharma, Sidhu, and Sharma 2015). The use of graphite powder and molybdenum disulfide is used in base oil for tuning of Inconel 718 using cemented carbide insert. Cutting force and surface roughness was analyzed by varying the flow rate of the mixture and the concentrations of the solid lubricant. Machining with molybdenum disulfide nanofluids resulted in reduction of cutting forces and surface characteristics (Marques et al. 2017). In another study the authors (Amrita et al. 2013) experimented using nano-graphite soluble oil on turning AISI 1040 steel and compared the results with dry lubrication and flood lubrication. Nano-graphite is added in three different weight percentage 0.1, 0.3 and 0.5% respectively in the base oil. The nanofluids penetrated effectively in the cutting zone due to the generation of aerosol which led to reduced chip-tool interface leading to reduced cutting force. Machining of nickel based alloy was reported with alumina and silver nanoparticles enriched nanofluids. The result were further compared with emulsion alone and dry machine. In case of alumina, reduced cutting force was obtained owing to small contact angle and lower spreadability behavior (Chetan et al. 2016). From the literature it can be seen that use of nanofluids in MQL is used by different authors for optimizing the machining parameters in turning operation. The use of machine learning technique in predicting the response parameters in turning with minimum quantity lubrication is scarcely used, which can save time, money and energy consumed in performing experimentation. Therefore in the present study, turning is carried out using alumina in biodegradable based vegetable oil under minimum quantity lubrication strategy on AISI 304 steel. The different combination of input parameters (feed, depth of cut, cutting speed and nanoparticle concentration) used for measuring the cutting force. The cutting forces are further predicted by using different machine learning methods such as linear regression (LR), random forest (RF) and support vector machine (SVM). Three different performance indicators are used to access the accuracy of different models.

MATERIALS AND METHODOLOGY

The turning operation is performed on conventional lathe machine. The workpiece for machining is selected as AISI 304 steel rod of 50mm diameter. The chemical constituents of AISI 304 steel is given in Table 1. The experiments are conducted in minimum quantity lubrication environment, which comprises of a spray nozzle, pressure regulator and compressor. The colloidal suspension of 20vol. % alumina nanoparticles in water having average particle size of 40nm is used in vegetable based oil for the preparation of the cutting fluid. Three different volumetric concentrations (0.25%, 0.75% and 1.25%) of cutting fluid were made for machining purpose. The cutting tool insert of tungsten carbide (CNMG 120408) clamped on widax tool holder is used for turning of AISI 304 steel.

Table 1. AISI 304 steel chemical constituents.

Element	Iron (Fe)	Chromium (Cr)	Nickel (Ni)	Manganese (Mn)	Silicon (Si)	Nitrogen (N)	Carbon (C)	Phosphorous (P)	Sulphur (S)
Percentage composition	Balanced	18-20	8-10.5	2	1	0.11	0.07	0.05	0.03

All the experiments were performed thrice and the average value of cutting force is recorded. The cutting force is measured using piezoelectric based Kistler force dynamometer (9257-B). For the purpose of modelling and analysis response surface methodology (RSM) is used which is a collection of statistical techniques for establishing relation between responses and input variables. The design of experiment using 4 factor (cutting speed, feed rate, depth of cut and nanoparticle concentration) and 3 levels (low, medium and high) is made and a total of 27 experiment are planned using the box-behenken approach with design expert software. The different factors and levels for experimentation is mentioned in Table 2.

Table 2. Different factors and levels for turning.

Factors/Levels	**low**	**medium**	**high**
(V_s)	(60)	(90)	(120)
(f)	(0.08)	(0.12)	(0.16)
(a_o)	(0.6)	(0.9)	(1.2)
(Np%)	(0.25)	(0.75)	(1.25)

Machine learning Techniques used for predicting the cutting force.

Linear Regression (LR)

This regression algorithm falls into the category of supervised learning. This algorithm aids in predictive modelling by which relationship between input and corresponding target variable can be established. In this model is trained for predicting the behavior of the data points depending upon the variables. It also helps in forecasting the change in the target variable based on the changes done in one or more input variable.

Random Forest (RF)

Random forest is a machine learning algorithm based on ensemble learning which combines multiple classifiers for solving the problem and enhance the performance of the model. This group learning approach utilizes bootstrap samples from a training dataset for creating forest of decision trees (Azure et al. 2021). The decision nodes and leaves explains the decision tree, where leaves represent the final outcome and decision nodes are the points where the data is split. This model is widely used owing to its simplicity and diversity which is used for both regression and classification.

Support vector Machine (SVM)

This machine learning model is proposed by Vapnik (Jurkovic et al. 2018). Support vector machine is used for prediction of discrete values and is a type of supervised learning algorithm. Support vector regression is a technique lying under the domain of support vector machine. The main aim of this technique is to get the line of best fit which is a hyperplane having maximum number of points as shown in Figure 1. In order to frame the hyperplane SVR selects extreme points /vectors and these extreme points are termed as support vectors and thus justifies the nomenclature of the technique. Support vector regression aims to fit the best line in the range of threshold value, which is the distance between the boundary line and the hyperplane.

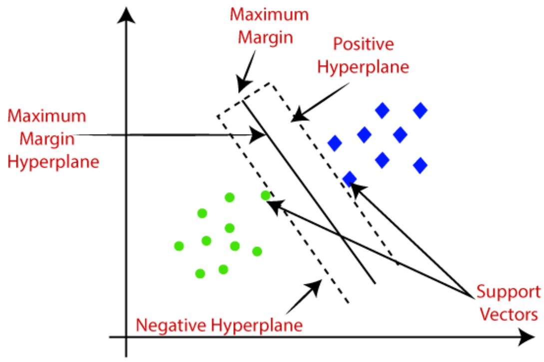

Figure 1. Graphical representation of Support Vector Machine.

Three different performance indicators are selected for judging the accuracy of the models in predicting the cutting force values which are coefficient of determination (R^2), mean absolute percentage error (MAPE) and mean square error (MSE) as given in Equation (1), (2) and (3) respectively.

$$R^2 = 1 - \frac{\sum_{i=1}^{n} (Yi - \hat{Y})^2}{\sum_{i=1}^{n} (Yi - \bar{Y})^2} \qquad (1)$$

$$MAPE = \frac{1}{n}\sum_{i=1}^{n} \frac{|Yi - \hat{Y}i|}{Yi} \times 100 \qquad (2)$$

$$MSE = \frac{1}{n}\sum_{i=1}^{n} (Yi - \hat{Y})^2 \qquad (3)$$

Where n is no. of data points, Yi represent observed values, $\hat{Y}$ represent predicted values and $\bar{Y}$ signifies the mean value of Y respectively.

RESULTS AND DISCUSSIONS

In this paper, response parameter is mainly cutting force which comes under non-beneficial category therefore, it should be minimum. To minimize it, proper lubrication and cooling is required at the machining interface. Therefore, in the present paper alumina nanofluid with MQL setup is used for cooling and lubrication purpose. The response table is shown in Table 3.

Table 3. Experimental design for MQL turning.

Experiment number	Vs(m/min)	f (mm/rev)	a_o (mm)	Np (%)	Cutting Force(N)
1	90	0.16	1.2	0.75	458.971
2	60	0.12	1.2	0.75	413.744
3	120	0.12	0.9	1.25	280.184
4	60	0.12	0.6	0.75	223.555
5	90	0.12	0.9	0.75	314.264
6	60	0.12	0.9	0.25	387.054
7	120	0.12	1.2	0.75	413.502
8	120	0.08	0.9	0.75	225.645
9	90	0.08	1.2	0.75	304.976
10	60	0.08	0.9	0.75	226.912
11	90	0.12	0.9	0.75	302.709
12	120	0.12	0.9	0.25	351.076
13	90	0.12	1.2	1.25	404.654
14	90	0.12	0.9	0.75	300.314
15	60	0.16	0.9	0.75	384.723
16	120	0.12	0.6	0.75	150.695
17	90	0.12	0.6	0.25	190.610
18	90	0.08	0.6	0.75	120.871
19	90	0.08	0.9	0.25	258.584
20	90	0.08	0.9	1.25	220.733
21	60	0.12	0.9	1.25	285.828
22	90	0.12	1.2	0.25	421.471
23	90	0.12	0.6	1.25	173.423
24	90	0.16	0.6	0.75	206.019
25	90	0.16	0.9	1.25	359.485
26	90	0.16	0.9	0.25	390.997
27	120	0.16	0.9	0.75	358.077

After getting response parameter (Table 3), the quadratic model has been developed for the analysis of variance to check the stability and significance of the response as well as process parameter using response surface methodology. The mathematical model for response parameters is discussed in Equation (4) given below:

$$\text{Cutting force} = -36-3.81Vs + 2874f +383a_o -174.3*Np\% + 0.01028Vs* Vs - 8671f * f * 200.7a_o * a_o + 48.6\, Np\% * Np\% - 5.29Vs * f + 2.017Vs * a_o +0.506Vs * Np\% + 1434f * a_o +79f * Np\% +0.6\, a_o * Np\%. \quad (4)$$

Now, analysis of variance is required to analysis the significance and influence of process parameters and their factors on response parameters. ANOVA was carried out at 95% confidence level that means the P- value of the factors must be less than 0.05 to satisfy the condition of significant factor criteria. Coefficient of determinant i.e., R2 and adjusted R2 is also one of the parameters to show the significance of experimental results. Regression model help to calculate coefficient of determinant and it should be more the 80% because for the experimental results 80% is in acceptable limit.

Table 4. ANOVA of cutting force

Source	DF	Adj SS	Adj MS	F-Value	P-Value	Percentage contribution
Model	14	222554	15897	54.30	0.000	
Linear	4	213785	53446	182.56	0.000	
Cutting Speed	1	1695	1695	5.79	0.033	0.749
Feed rate	1	53407	53407	182.43	0.000	23.62
Depth of cut	1	152358	152358	520.43	0.000	67.39
Np conc%	1	6324	6324	21.60	0.001	2.797
Square	4	5865	1466	5.01	0.013	
Cutting Speed*Cutting Speed	1	457	457	1.56	0.236	0.202
Feed rate*Feed rate	1	1027	1027	3.51	0.086	0.454
Depth of cut*Depth of cut	1	1740	1740	5.94	0.031	0.769
Np conc%*Np conc%	1	786	786	2.68	0.127	0.347
2-Way Interaction	6	2904	484	1.65	0.216	
Cutting Speed*Feed rate	1	161	161	0.55	0.473	0.071
Cutting Speed*Depth of cut	1	1318	1318	4.50	0.055	0.583
Cutting Speed*Np conc%	1	230	230	0.79	0.393	0.101
Feed rate*Depth of cut	1	1185	1185	4.05	0.067	0.524
Feed rate*Np conc%	1	10	10	0.03	0.856	0.004
Depth of cut*Np conc%	1	0	0	0.00	0.992	
Error	12	3513	293			
Lack-of-Fit	10	3402	340	6.11	0.149	
Pure Error	2	111	56			
Total	26	226067				

In table 4, analysis of variance for force has been done to analyze the significance of the process parameter and their impact on response parameter i.e., force. Table 4 signify that depth of cut having major impression on cutting force approximately 67.39% which is highest among all of the process parameters and their factors. Coefficient of determinant also use to show the significance and accuracy of experimental results, if R^2 and adjusted R^2 is greater than 90% the output is acceptable. In case of cutting force R^2 is 98.45% and adjusted R2 is 96.63%.

Prediction of response (cutting force) by different machine learning models.

The cutting force obtained from turning operation has been predicted using three different regression based machine learning models. The total number of data points are 27 that are used for model creation and evaluation. Two-thirds (2/3) of the input data were picked at random for model construction (training). The model was validated using the remaining 1/3 of the input data (testing). In predicting cutting force by different models, four different input variables are used namely feed, depth of cut, cutting speed and nanoparticle concentration. In order to minimize the error that may arise due to the unit differences of the input parameters, scaling has been performed of both training and testing data using standard scalar. For ensuring best parameter for our model, cross validation has been performed using GridSearchCV.

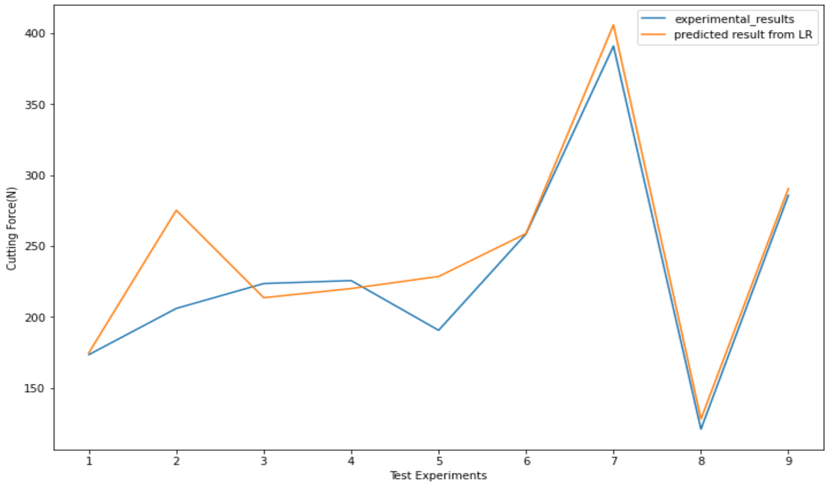

Figure 2. Predicted values from linear regression

In case of linear regression as shown in Figure 2, the comparative graph is plotted between experimental values of cutting force and the predicted values obtained from linear regression. As per the performance indicators, R^2 is 0.8587, MAPE for the model is 0.0808 and MSE is 739.97 for the test data.

For prediction of cutting forces using random forest, bootstrap aggregation is employed. The predicted values by random forest technique is depicted in Figure 3. The R^2, MAPE and MSE in this case are 0.1307, 0.2423 and 4551.98 respectively.

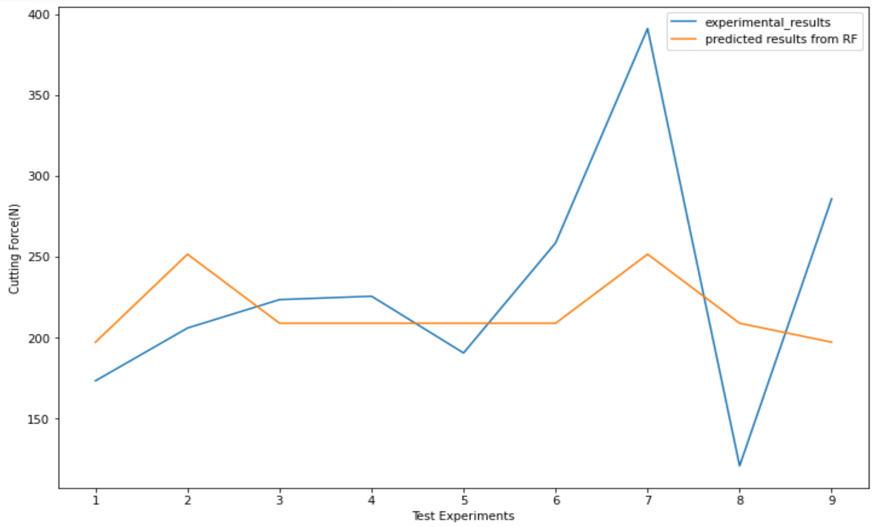

Figure 3. Predicted value from random forest

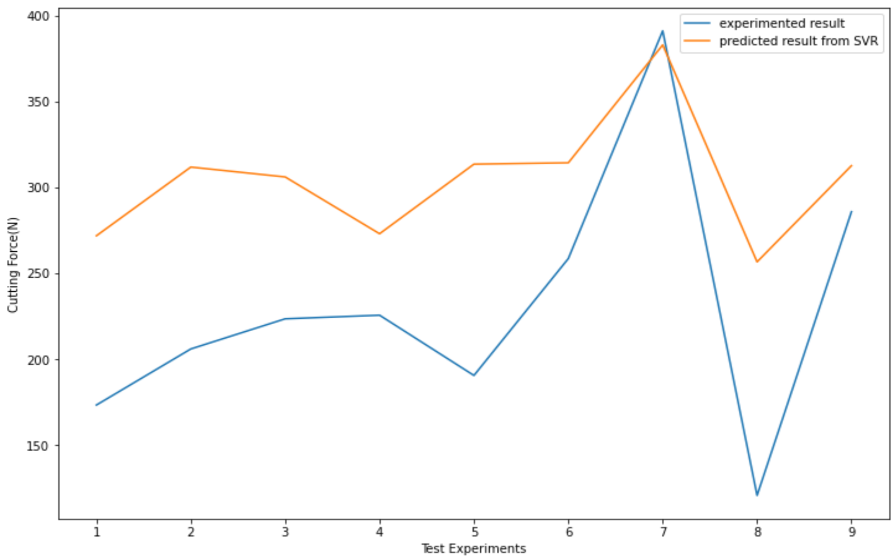

Figure 4. Predicted value from SVR

Similarly, the predicted cutting force of MQL turning are shown in Figure 4 by support vector regression. For judging the accuracy of the model the three indicators represented R^2 -0.4282, MAPE as 0.4175 and MSE as 7482.033. The predicted values from three different models are compared in Figure 5 and tabulated in Table 5.

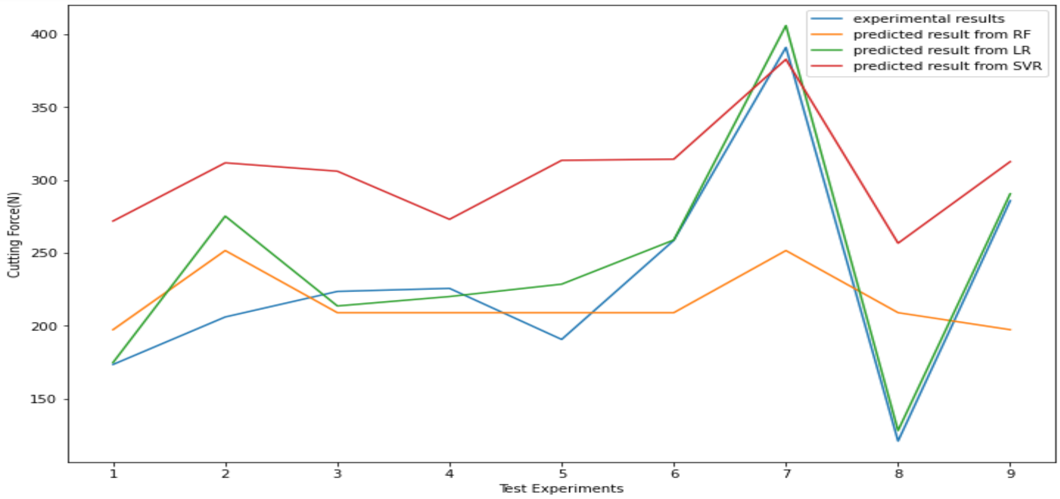

Figure 5. Comparative predicted value from all three machine learning algorithm.

Table 5. Predicted values from different machine learning algorithm

Exp. no.	Test exp.	Exp. Value	LR	RF	SVR
23	1	173.42	174.77	197.28	271.84
24	2	206.01	275.22	251.60	311.78
4	3	223.55	213.56	208.96	306.03
8	4	225.64	220.03	208.96	273.00
17	5	190.60	228.53	208.96	313.48
19	6	258.58	258.82	208.96	314.27
26	7	390.99	405.97	251.60	382.82
18	8	120.87	128.07	208.96	256.64
21	9	285.82	290.56	197.28	312.60

CONCLUSION

The machining of AISI 304 steel is conducted in mist lubrication environment and cutting force is measured using the force dynamometer. The cutting force is predicted using the different machine learning algorithm. The following conclusions can be drawn from the study:

- It can be deduced from the ANOVA table that depth of cut is the significant parameter in evaluating cutting force.
- Linear regression and RFs are more accurate than the SVR in making predictions of the cutting force.
- The performance indicators suggested that linear regression outperformed in comparison to the other two models as it possessed R^2 closer to 1 and minimum MAPE and MSE value.

Further it can be summarized that the output of a certain machine learning technique is also influenced by the type of the data gathered. There are several instances where one approach is preferable for one dataset but not for another. Every machine learning approach has its own unique features. Furthermore the prediction of more response parameters like surface roughness, tool tip temperature with different cooling strategies like cryogenic cooling and high pressure cooling can be explored using machine learning techniques.

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