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# Review on Modelling of Cutting Parameter using Machine Learning.

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**ABSTRACT:** This review paper give idea about how we will study and develop model on machine learning in predictive maintenance. With the help machine learning algorithm., Random Forest, Gaussian Process Regression (GPR), and Support vector machines (SVM), along with simulation software AdvantEdge a cutting force prediction model for cutting operation can be built in this study. Machining process data can be utilized to predict cutting force and optimize process parameters. Cutting force is an essential parameter that has a significant impact on the metal operation process.

**KEYWORDS:** Machine learning, Predictive, Cutting Force.

## I. INTRODUCTION

Machining is an essential procedure for component production and precision. Because of the significant increase in production time, machining has become increasingly important in today's automated manufacturing systems, as has the need to recoup the significant initial investment in these modern technologies. In most circumstances, turning is a pretty basic motion that produces cylindrical surfaces. Turning is one of the most commonly utilised processes in experimental work and metal cutting. The device is rigidly held in a device submit and moved at a steady tempo alongside the axis of the bar while the element is turned, removing a layer of steel to form a floor or a more advanced profile. After going through the first round of processing, which includes casting, forging, and extrusion, [2]. As a result, precise cutting force prediction during turning becomes a critical aspect for process optimization and characterization, as well as enhancing machining efficiency. Furthermore, creating a predictive model is quite big challenge to gain insights due to the numerous connected input parameters that determine the cutting force, such as feed rate, cutting depth, cutting speed, nose radius, and cutting-edge angles [3]. As a result, accurate cutting force prediction during turning becomes a vital feature for process optimization and characterization, as well as machining efficiency improvement.

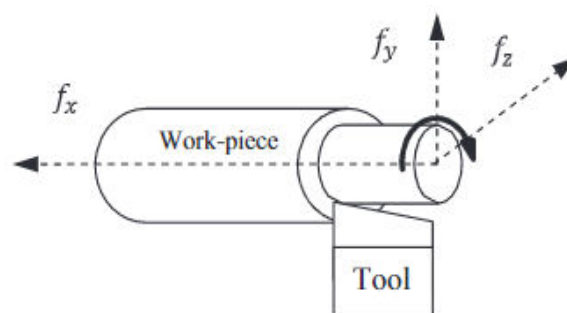


Fig. 1. Direction of forces in turning operation.

The life of a cutting tool is greatly influenced by the forces acting on it during a cutting operation. Amachining operation is a complex process. It is very difficult to develop a comprehensive model involving all the parameters. Hence necessary to gain insights of cutting parameter before operation for proper maintenance of the environment.

## II. RELATED WORK

Several investigations to model the machining process parameters in the turning process exist in the literature. Alwin Varghese et.al. [5] studied proposes a method involving the use of cutting force data alone to verify the micro-milling tool's usefulness by detecting tool-life stages without breakage. The proposed methodology is based on a novel simple and dependable algorithm that was just proposed. on k-means clustering to automate the identification of machining data from the raw data. Random Forest model provided the most reliable prediction of tool life stage with 88.5% prediction accuracy compared to SVM and LR in effect. Hanief et al. [6] established a model to examine the impact of cutting parameters on During the red brass turning, a high-speed steel (HSS) instrument was used to cut the force process (C23000). Multiple regression as well as artificial neural network (ANN) techniques were used it was concluded that the ANN model can predict the cutting forces more accurately that the regression model with the accuracy of 99.962 %. A.D. Patange et.al. [7] used machine learning based condition monitoring of milling cutter of vertical machining Centre (VMC) was successfully demonstrated. The vibration signals acquisition for milling cutter was carried out with fault tool conditions. The statistical features are extracted using Visual Basic (VB) code and script, and the relevant features are selected using the decision tree technique. The different conditions of tool are classified using tree family classifiers J48, LMT and random forest algorithms. Considering the classification accuracy and time required to build the model, the random forest observed to be best classifier. The LMT classifier yields slightly more accuracy than random forest but time required is considerably more than the random forest classifier. Paschalis Charalampous[8] provided methodology for delivering data and knowledge regarding the relationships between produced cutting forces and cutting circumstances including cutting speed, radial depth of cut, and feed rate. First, an experimental dataset was developed on face milling AISI 4140 QT with a wide range of cutting conditions. The results have revealed that the best performance was achieved with SVR algorithm. Baviskar et.al. [9] The turning experiment was carried out on a CNC Lathe machine using tungsten carbide (uncoated and coated with Al<sub>2</sub>O<sub>3</sub>) tool inserts and AISI 4340 as the work piece material. In order to accomplish tool life, surface roughness, and tool forces generated on tool inserts, it used a full factorial design of experiment. Cutting speed, feed, and depth of cut are three cutting characteristics that are considered influencing factors. They discovered that feed has a substantial impact on feed force, cutting speed has a significant impact on cutting force, depth of cut has a significant impact on thrust force, and feed has a significant impact on surface roughness. ANN model proved to provide a better prediction with overall error within 10% even though ANN is predicting outcomes effectively, the regression model's percentage error is less than 15%, demonstrating that mathematical models are particularly effective in machining operations for forecasting results. Bingxiao Peng et.al. [10] used hybrid approach using a supervised machine learning model (ML) for predicting the specific cutting forces was introduced. To achieve continuous training of new data sets, a batch system using a Deep Neutron Network (DNN) was deployed. Experiments in orthogonal cutting and 2D FEM chip formation simulations were utilized as hybrid data sources. Where they found that Compared to the conventional linear regression model, an accurate Using a machine learning model, it was possible to forecast certain cutting forces provided an accuracy of 97.7% and concluded that compared to the conventional linear regression model, an accurate prediction of the specific cutting forces was achieved by using the machine learning model.

Sharma et al. [11] suggested a prediction model for the cutting force for hard turning operations. The ANOVA research in this paper demonstrated how each machining parameter affects the calculation and analysis of cutting force. The established fuzzy model was considered to be satisfactory and better than the regression model for estimation purposes. L.W. Hernández-González [17] proposed Modelling Cutting Forces in High-Speed Turning using Artificial Neural Network (ANN). For these cutting forces, and the Specific Energy Consumption (SEC) during the dry high-speed turning of AISI 1045 steel were modelled using a function fitting neural network topology. Cutting forces were measured experimentally and compared to predictions from predictive models constructed with polynomial regression and artificial neural networks. Their findings showed good reliability of FFNN models in predicting SEC under various machining conditions. Their results confirm the complexity of the machining process, which depends on a considerable number of factors. Mahdi. S. Alajmi et.al. [19] used above experimental data and developed a machine learning algorithm for force prediction by taking combination of four cutting parameters from were found that the Gaussian process regression (GPR) approach was utilized to model and predict cutting force in the turning process of AISI 4340 alloy steel. The accuracy of the model and tested against other methods such as SVM and ANN. GPR provided better accuracy of 98.43% . The results suggest that the GPR could be utilized by process operators to predict cutting force parameters prior improve the manufacturing process in order to conserve resources, and to design the experiment in

order to provide the needed output quality. Fodor et al. [20] revealed how to describe the cutting force in material-eliminating systems using Gaussian white noise stochastic processes. This method aids in the solution of mathematically dynamic stochastic differential equations. The results revealed that computed force signal's variability is typically in the range of 4–9% of the average. A value that is higher than the noise generated by the measuring equipment. Chen et al. [21] To monitor and anticipate tool wear in the drilling process, a hybrid approach based on adaptive particle swarm optimization, a least squares algorithm, and a support vector machine (APSO-LS-SVM) was presented. To process the sample data related to drill wear state, multiple signal feature extraction algorithms are used. The tool wear identification model has a mean absolute error of 0.91 percent, which is lower than the typical LS-SVM approach under the identical conditions. Table 1 shows the overall parameter and model used.

Table 1.

SR NO	AUTHOR AND YEAR OF PUBLICATION	MACHINING CONDITION	OUTPUT PARAMETER	AI MODEL	RESULT
1	MAHDI. S. ALAJMI ABDULLAH. ALMESHAL (2021)	Cutting speed, Nose radius, Feed rate, Depth of cut, Surface Roughness	Average cutting force	GPR ANN Model	The GPR outperformed methods with A high degree of accuracy
2	K.A. BAVISKAR U.S. CHAVAN DEEPAK KULKARNI (2019)	Cutting speed Depth Speed on turning operation	Cutting forces And surface roughness	ANN	Model was 93% was accurate
3	ALWIN VARGHESE VINAY KULKARNI SUHAS S. JOSHI (2021)	Cutting force on Milling operation	Tool wear and tool life stages	RF, LR, ANN, SVM	88.5% prediction accuracy of RF
4	SHUBHAM VAISHNAV ANKIT AGARWAL K. A. DESAI (2019)	Cutting force on end milling operation	TOOL LIFE	NN Method	Model can predict instantaneous cutting forces effectively
5	M. HANIEF M.F. WANI M.S. CHAROO (2016)	Feed Speed Depth of cut on Turning operation	Cutting forces	ANN	The mean square error in ANN model was found to be 0.0059
6	A.D. PATANGE A.A. TADAMALLE S.S. MULIK (2020)	Feed Depth of cut Cutting speed on VMC	Cutting forces	RF	Accuracy was 86%
7	MAIK FRYE ROBERT H. SCHMITT (2019)	Cutting force on milling operation	Tool life	RF LSTM neural network	RF model was 93% accurate
8	PASCHALIS CHARALAMPOUS (2021)	Milling operation	Cutting force	RF and SVR	RF model accurate than SVR
9	MARTINEZ ALLERANO G. TERRAZES P. BERNANDOS S. RATCHEV (2018)	Cutting speed Depth Speed on turning operation	Average cutting forces and tool wear	CNN	Model 90% accurate



10	BINGXIAO PENG THOMAS BERGSA DANIEL SCHRAKNEPPER FRITZ KLOCKE BENJAMIN (2019)	Cutting speed Undeformed chip thickness Rake angle Clearance angle Cutting edge radius Flank wear	Cutting forces	DNN along with FEM	FEM simulations are running to train the ML model
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### III. METHODOLOGY

Predictive maintenance cannot exist without condition monitoring, which is defined as the continuous monitoring of machines during process conditions to ensure the optimal use of machines. There are three facets of condition monitoring: online, periodic and remote. Online condition monitoring is defined as the continuous monitoring of machines or production processes, with data collected on critical speeds and changing spindle positions. preventive maintenance does not demand the condition monitoring component that predictive maintenance does. By not requiring condition monitoring, a preventive maintenance program does not involve as much capital investment in technology and training. Lastly, many preventive maintenance programs need manual data-gathering and analysing. Figure 2 shows predictive cycle.

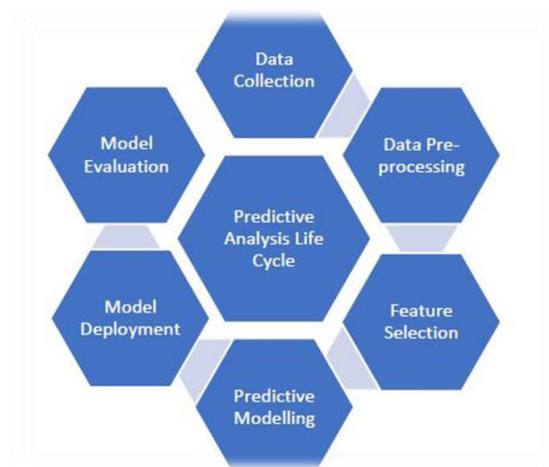
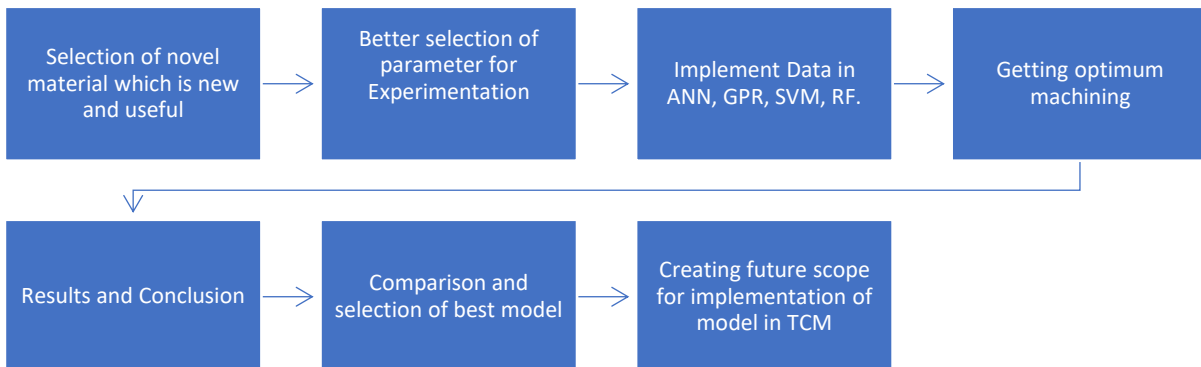


Figure 2. Predictive Cycle

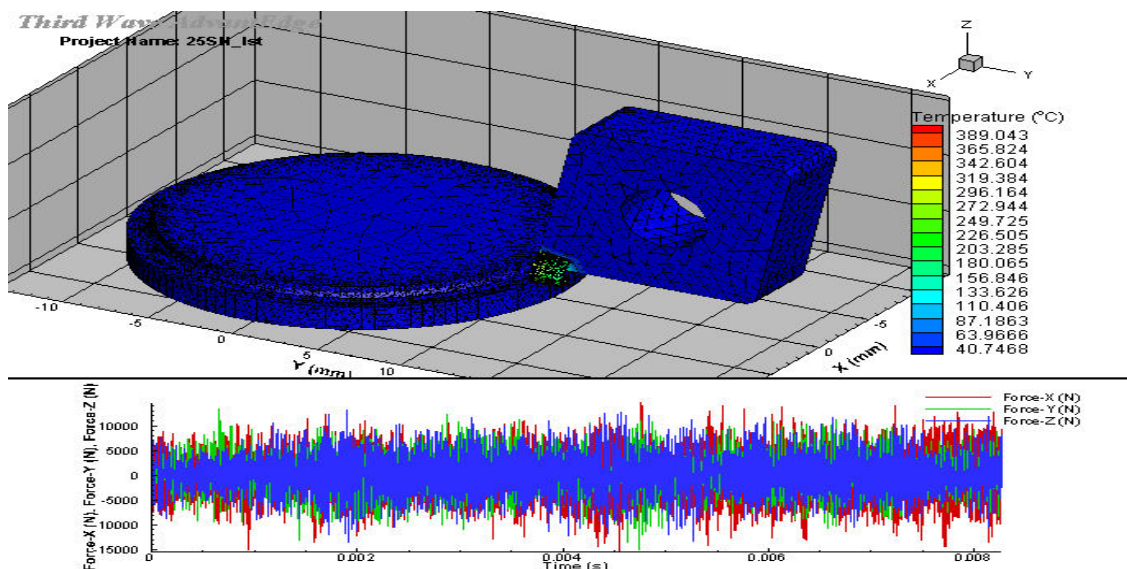


**Figure3.**Machine Learning approach to predict cutting Force.

Machine learning approach is show in Figure3 which shows the right from selection of material to the testing and validation of model. Predictive maintenance also requires more investments in people, training and equipment than preventive maintenance, but the time savings and cost savings will be greater in the long run.

#### IV. MODIFICATION AND SIMULATION FOR DATA CREATION

Checking accuracy for unknown Data sets by simulation. By dividing data set for training of model and testing, we get result. But for unknown data set accuracy has to be tested for which new machining data has produced. Exact repetition of experimental setup is not feasible so finite element analysis (FEA) software is used named AdvantEdge7.1. This software is particularly designed for standard machining process simulation i.e., milling, turning, boring, drilling etc. Same machining conditions are simulated for different machining conditions in AdvantEdge software. This error will add to new data set for the making of more accurate machining data. The simulation of AdvantEdge is shown in Figure 3, for taking data response parameter. The data of the Forces is extracted from AdvantEdge for unknown Forces prediction using various machine learning algorithm to check accuracy.



**Figure4.**Simulation using Advantedge

Texture tool increases the tool life so machine learning approach should be used to predict cutting forces. Creating Tool Data with Micro-cavities of Circular shape, triangular shape on Tool Surface with the parameters like dimple size, pitch, depth, and distance from the cutting edge. Taguchi Designs and ANOVA (using Minitab) to determine the most optimal parameter data configuration. Simulating using FEA application named AdvantEdge for Data creation for Machine Learning Model.

## V. CONCLUSION

To have real time Implementing Tool Condition Monitoring (TCM). To create an effective model because of the multiple interrelated parameters. The vibration parameter, surface roughness, nose radius wear and its initial conditions which was lacking can be acquired from accelerometer and various sensors for the data acquisition. Vibrations and acoustic emission can be further experimented for increasing the size of the training and test sets. The vibration data acquired with a combination of faulty and new inserts method. Model which is applicable for any type of workpiece material or cutting tool provided that appropriate data is available during the training process. In other words, to apply this method the learning component needs to be trained on the behaviors of the combination of the selected tool and workpiece. To create Gaussian Process Regression (GPR) and Support Vector Method (SVM), Random Forest which is more efficient and reliable model which has high degree of accuracy. Finally, integration of the self-adaptive component will be undertaken. While many organizations choose to train existing employees on predictive maintenance, there are condition-monitoring contractors who specialize in performing the required labour and analysing the results for a facility. In addition to the training costs, predictive maintenance involves an investment in maintenance tools and systems. This cost has decreased over time with the introduction of cloud-based technology.

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