# Comparison of Machine Learning Algorithms in Predicting the Cutting Force for Thermal Assisted Machining of Ti6Al4V

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**Abstract**

This paper is focused to predict cutting force of the titanium alloy (Ti–6Al–4V) due to the effect of feed rate, speed and temperature during the machining operation. The design of experiments was used to generate various combinations of feed rate, speed and temperature. Finite element modeling (FEM) using Abaqus used for simulate the machining parameters. The obtained results from FEM model and the experimental work are used to train the model using machine learning algorithm. The trained model is allowed to predict cutting force for various combinations of feed rate, speed and temperature. To verify the accuracy, regression analysis has been adopted in the paper to develop a second prediction model for cutting force.

*Keywords*: FEM Model, DTM(Difficult to machining), Mean Square Error.

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## 1. Introduction

Titanium alloy (Ti–6Al–4V) used commonly in aerospace and other industries because of low density, light weight, high-specific strength, which is maintained at elevated temperature, exceptional resistance to corrosion, and its fracture resistant characteristics. . Machining of titanium alloy (Ti–6Al–4V) is widely applied in the aerospace industry. Increasing demand of titanium alloy machining is also increasing there by in other industrial and commercial applications.Simulation models are very important in the machining process as comprehension and for the reduction of experimental tests necessary for the optimization of tool geometries, cutting conditions and other parameters like the choice of the tool material and coating thus, a finer simulation enables good predictions in the cutting force. This will contribute to cost reductions for the machining process optimization that are still experimentally done and thus expensive.Therefore, researchers are focusing on modeling and simulation techniques to predict and optimize cutting force. These techniques do not need to perform many experimental tests that will cost a lot of money and are time consuming. Besides that, researchers are usually seeking to use a wide range of tools and techniques to ensure that the designs they have created are safe.

Industries need to know whether a product failed because the design was inadequate or due to another cause such as human error. Nevertheless, they have to ensure that the product works well under a wide range of conditions and try to avoid failure due to any cause. In this respect, finite element modeling (FEM) could help to avoid failure.

$$(x+a)^n = \sum_{k=0}^{n} \binom{n}{k} x^k a^{n-k} \qquad (1)$$

FEM is a very important technique for estimating stress–strain analysis because it can produce very accurate results.The main objective of this research work was to predict cutting force during orthogonal machining operation of the titanium alloy (Ti–6Al–4V). Hence, a predictive model was developed by using the finite element modeling (FEM) under dry cutting conditions when using machining parameter variables such as feed rate, cutting speed and temperature.

In the present study, machine learning and finite elements models were used for predicting the cutting force (dependent variable) during the machining process with regard to the cutting conditions (independent variables) like feed rate, radius depth and cutting speed. The experimental results from the machining investigations were filtered and fed into machine learning algorithms creating trustworthy predictive models.It was found that machine learning models can estimate the complicated interactions of the cutting conditions on the developed cutting forces with notable accuracy. It has to be noted that the production of high-quality end products coupled with minimum cost is a timeless manufacturing target. Industry 4.0 has already exhibited its potentials via the utilization of core technologies such as Industrial AI and Machine Learning in order to reach the above-mentioned goal more successfully than ever. Data mining has become a worthwhile resource, and the acquisition as well the store of data is cheaper compared to previous decades. Therefore, through the employment of process-based machine learning algorithms, manufacturers could utilize data to enhance the product quality and production efficiency.In general, the productivity in machining procedures is mainly restricted be the tools wear which is induced by the development of high cutting forces during the process. Hence, engineers should take into account the developed milling forces as an indirect sign for the state of the cutting tool and the quality of the manufacturing procedure.

In the present research, a novel approach based on machine learning algorithms and FE models is proposed providing crucial information on the expected cutting forces on the tool based only on previously stored data of the process, preventing that way the integration of additional new sensors on the machine center.The experimental setup is described combined with the results of the machining tests collecting that way the dataset for the development of the machine learning models. Finally, the developed machine learning and finite element models are demonstrated coupled with their results.Numbers and constant names should be written in a simple font, such as 2.3456. Vectors should also be bold, and variable names should be italicised. The numbers in the formula should line up with the right margin, for example:

Note: Explanation of each term can be explained here.

## 2. Numerical Validation

### 2.1 FEM Model

Because of advances in computational efficiency and speed, finite element techniques (FEM) have become widely used in academic and industry applications in recent years. When compared to analytical models, FEM-based simulations have numerous advantages. Finite element cutting simulations can estimate process variables that are difficult or impossible to measure directly during the cutting process, such as . These parameters must be determined in order to understand the mechanics of the cutting process and undertake tool wear analysis. . The numerical model is developed using ABAQUS/Explicit in this study. In order to estimate the impacts of machining parameters on the cutting force while the turning process of TI6Al4V alloy, a 2D numerical model is first created.

The workpiece is designed to be deformable, and the tool is designed to be analytically rigid. The tool's rake angle and clearance angle are assumed to be 5° and 5° degrees, respectively. Initially a mesh convergence study is conducted. Surface to surface interaction is employed in this investigation, with a constant friction coefficient of 0.24. The Input parameters selected for the operation are

**Cutting Speed –** 150 175 200 m/min

**Feed rate** – 0.1 0.15 0.2 mm/rev

**Temperature** - 500 600 700°C

The rake angle and clearance angle are maintained at 5°,which is in alignment with the journal used for validation The depth of Cut is maintained at 2.75mm.The Cutting force is selected as the output parameter.

| Feed Rate | Rake Angle | Speed (rpm) | Cutting Force (Coarse) | Cutting Force (Refined) | % Deviation |
|---|---|---|---|---|---|
| 0.1 | 5° | 1600 | 284.1 | 295.7 | 4.1 |

Table 1: Mesh Convergence Study

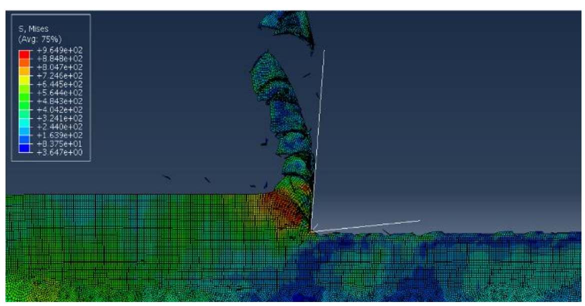


Figure 1: Finite Element Stress Contour Plot (Von Mises Stress Distribution)

The workpiece's lower and left edges are both subjected to an encastre boundary condition. As the boundary condition, a determined velocity value is applied to the reference point on the tool in the negative x-direction. The tool's vertical displacement and in-plane rotation are also restricted. CPE4RT elements of the plane strain element type are employed in the model. The fracture energy, which is used to quantify the material deterioration that occurs once damage occurs in a workpiece, is changed in this study until the simulation results show a satisfactory agreement with the experimental results under the given cutting conditions. . In detail, on the given mesh condition, the initial value for fracture energy is estimated.

Simulations are carried out for combinations of machining parameters and validated the FE model results by comparing the values with experimental results. The maximum deviation is found to be 3.4%.In the validated model, by changing the tool and workpiece geometry and modifying the fracture energy value based on values in paper and simulations are run for all combinations obtained from Minitab for different optimization techniques. Cutting forces are measured as reaction forces at the reference point on the tool.

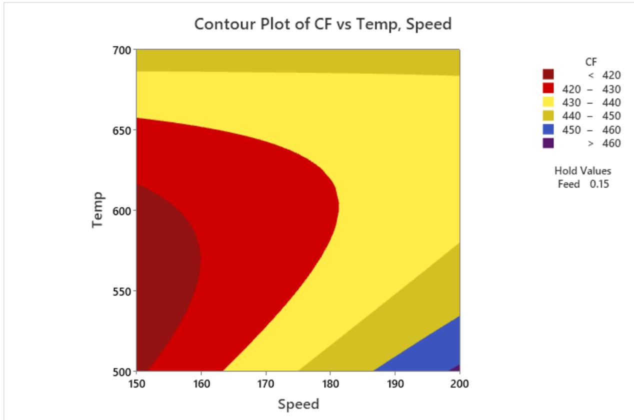


Figure 2: Contour Plotof CF vs Temp,Speed

### A. Thermal Assisted machining

Recently, TAM has been used as an auxiliary process for machining various DTM materials and alloys as well as alloys possess high melting point, and composites . TAM deploys a intense heat focussed at a certain spot on the workpiece to preheat upstream of tool path surface during traditional machining.

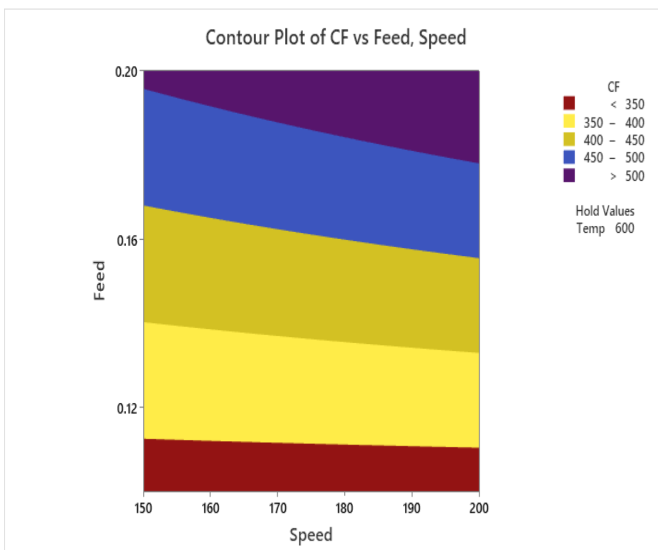


Figure 3: Contour Plot of CF vs Feed,Speed

This localized heating lowers the yield strength of DTM(Difficult to machining) at elevated temperature, thus reducing cutting forces and tool wear to improve surface finish quality and cut down the machining time. However, the intense heating causes oxidation, melting and/or vaporization of the workpiece surface while the transient thermal response of the workpiece would potentially induce uneven thermal expansion of the material.The performance of preheating technique depends on thermal power, beam diameter, scan speed and approach angle (tool-beam distance), well as the machining parameters such as cutting speed, feed rate and depth of cut.

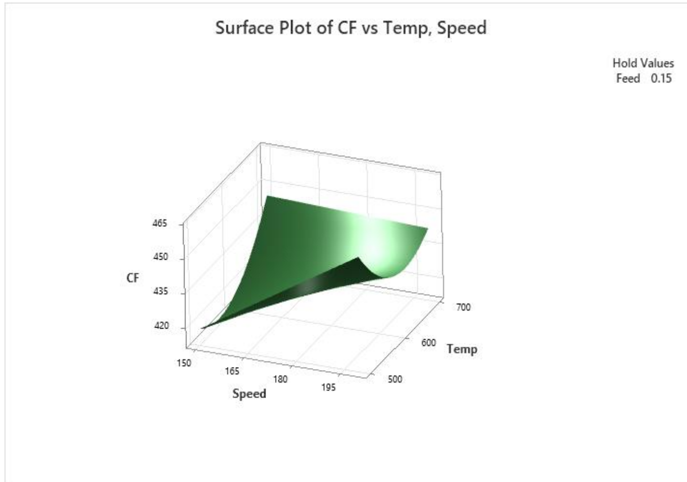


Figure 4.Surface plot of CF vs Temp,Speed

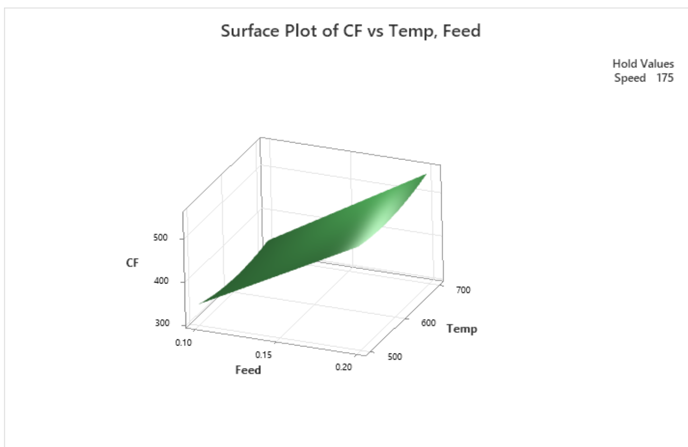


Figure 5.Surface plot of CF vs Temp,Feed

This technique has been widely extended to various machining operations such as milling, grinding and turning, etc., recognizing its many advantages: (i) adaptability to different types of machining processes, (ii) localization of high temperature and (iii) process stability, etc. This technique offers flexibility in machining of DTM material as it allows adjusting of input parameters to reduce machining time, thus yielding a significant reduction in production cost, as much as 60–80% .

In TAT thermal assisted turning, the workpiece rotates at high speed and while it is being subjected to cyclic heating at a specific rotating point via a laser beam focused on an area ahead of the cutting edge. The workpiece temperature gets progressively elevated at the heated point and shows slight cooling when moving away along the cutting path. Generally, a continuous-wave beam with a Gaussian distribution is useful to minimize the thermal shock. To the contrary, with a pulsed-wave mode laser, heating and cooling tend to be more rapid at the workpiece, leading to a workpiece surface hardening process that adversely affects the machining performance. The convection and conduction heat transfers processes impact considerably on the temperature distribution in the cutting zone. It has been found that arranging the heat source perpendicular to the feed direction is more effective for not heating the machined surface and makes machining easier. In addition, in this method, the heat output is regulated by a pyrometer, allowing a constant temperature to be achieved in the component. However, the temperature at a depth of machining may not be enough for a deeper cut and the measurements do not warrant recording such temperature for precise determination of effective cutting depth. Whilst TAM can be practically used for machining titanium alloys, this technique is observed to be difficult for cutting straight holes or pear-shaped holes .

Another possible arrangement of the heat source is to set it vertical orientation to the workpiece chamfer surface during turning operation. This reduces the components of cutting forces significantly, hence minimizing the chances of any mechanical and/or thermal issues. In thermal assisted milling operation, multiple heat source can be used in various orientations over the cutting area, because a large zone is covered by cutting tool. The temperature at the heat spot depends on (i) the heating duration, (ii) the thermal power density distribution and (iii) the number of heating/cooling cycles. Due to the ability to control spot size and thermal power density, the thermal distortion and heat-affected area are generally small with TAT methods. Therefore, intense thermal gradient is confined to a very thin surface layer at the workpiece, enabling machining without interfering on the integrity of workpiece subsurface. According to many studies, the temperature gradient at the cutting zone is important to understand the mechanism of chip formation, investigate the thermo-mechanical characteristics in TAM, and to determine the reduction values of cutting forces .

It has been noted that there are positive influences of TAM parameters on the machining of titanium alloys. Rising preheating temperature with thermal power causes a decrease the microhardness at machined zone, thereby reducing the cutting tool pressure on the workpiece surface. Subsequently, this leads to a significant reduction in cutting force and flank wear, thereby increasing cutting tool life. Moreover, the chip formation during TAM is continuous because of preheating temperature improves the deformability of workpiece surface layer near to cutting zone. Furthermore, lowering down dynamic cutting forces and hardness near the cutting surface leads to much smoother machined surface with very few defects such as material build-up and grain pull-out. TAM effectively improves the machinability of titanium alloys even at high cutting speed.

**3. ML Validation**

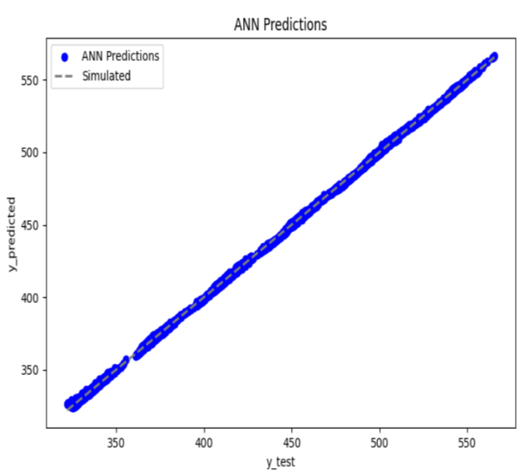


Figure 6.ANN Pedictions

Machine learning (ML) is a scientific area of artificial intelligence, which apply statistical and mathematical methods to offer computer systems the capability to learn from a set of data and predict the probability of a future event or a value, as well as to classify unseen data into a distinct number of classes. In the first step, machining experiments were conducted in various cutting conditions collecting the necessary dataset. In the preprocessing phase, the conversion of the raw data from the dynamometer into a clean dataset was taken place.

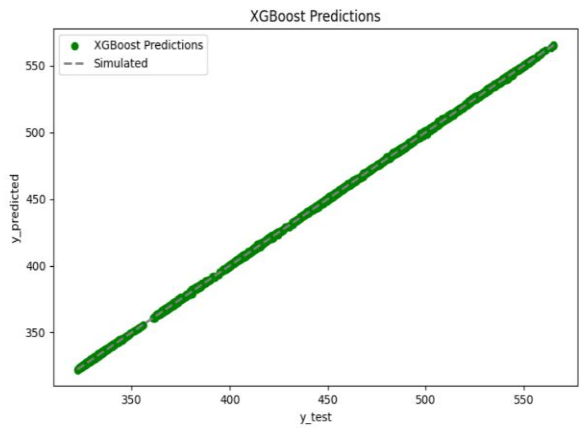


Figure 7.Xgoost Predictions

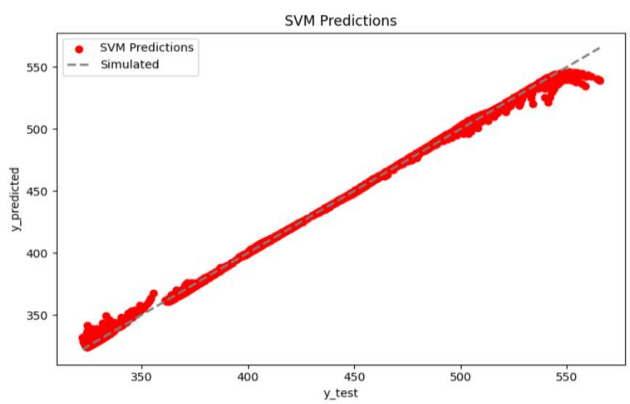


Figure 8.SVM Predictions

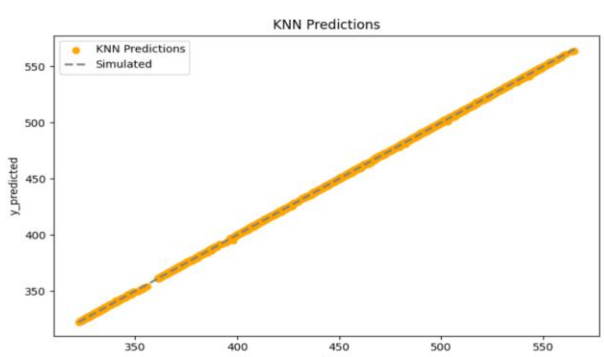


Figure 9.KNN Predictions

The training and the validation set. The training set contains instances used to train the ML models and the validation set to verify the accuracy of the developed predictive models on unseen data. Hence, the validation set consists of data which are unknown during the training set, avoiding that way the overfitting phenomenon. All of the applied ML algorithms have diverse parameters that need to be tuned in order to acquire their optimal performance. In the final step, the most efficient model possible was selected for the prediction of the cutting forces during the machining process.

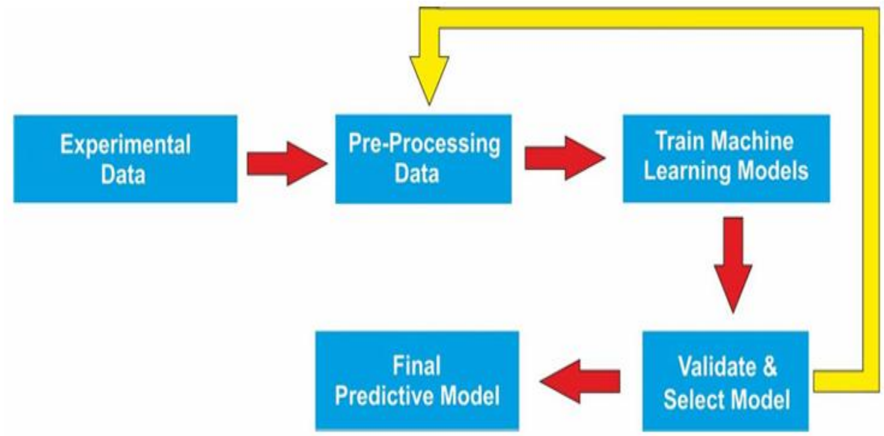


Figure 10: Machine learning approach to predict cutting force in orthogonal cutting

From the perspective of artificial intelligence, the prediction of milling forces is a regression problem. Four machine learning algorithms were employed to examine the effect of cutting conditions on the developed cutting forces in milling AISI 4140 QT. Random Forest (RF) is an ensemble ML method, which is applied in both classification and regression problems. In this algorithm, multiple decision trees are created using a fraction of the whole dataset and considered to compute a stable and reliable prediction. A decision tree splits the data along one direction according to some criterion, as it is shown schematically in Fig. Finally, the overall prediction of the algorithm is the average of the predictions from the individual trees (Ref 18). Support vector regression (SVR) is an expansion of the support vector machine (SVM) algorithms allowing to solve problems with continuous values. The main characteristics of the SVR algorithm.

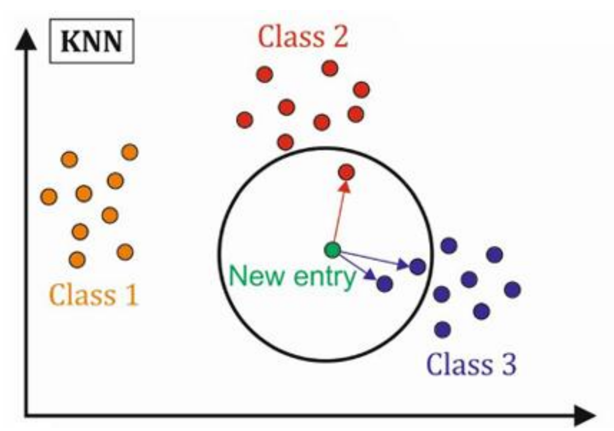


Figure 10.K-Nearest Neighbors (KNN) Classification Algorithm

The goal is to minimize the generalized error bound instead of minimizing the training error. This could be achieved by solving the optimization problem. K-nearest neighbor (KNN) is an algorithm that is applied in both regression and classifications tasks, and the predictions are based on correlation features (e.g., distance functions). The outcome of a new entry depends on how strong is its similarity with the training set.

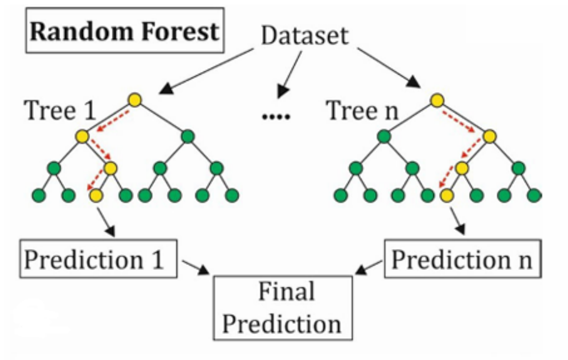


Figure 11.Random Forest Ensemble Learning Method

In the first step of the method, the distance between the new entry and each point of the training set is computed. In the next phase, the closest k (a parameter that is specified by the user) data points by means of a distance are preferred. Finally, the prediction is calculated by the average distance of the selected k data points. The last technique that was applied in the present research was the polynomial regressor.Polynomial models are suitable when the relationship between the explanatory and the response variables is curvilinear or nonlinear in case where the ranges of the explanatory variables are restricted. The higher the degree of the polynomial, the better is the fit of the regressor; however, high-order polynomials are more likely to overfit.

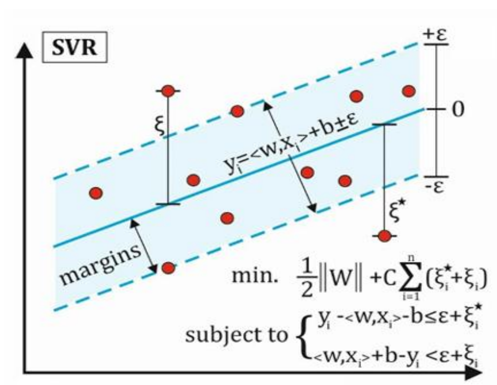


Figure 12.Support Vector Regression (SVR) Model

Moreover, the performance of the ML models regarding the prediction of the cutting forces in the machining process . Three criteria, Mean Square Error (MSE), Mean Absolute Error (MAE) and the errors between the predicted and the actual experimental values were used in order to evaluate the forecasting efficiency. The parameters of the employed ML algorithms were tuned via cross-validated grid search.As shown from the results, the best performance was recorded from the SVR, followed by the KNN, the Polynomial Regressor (PR) and lastly the Random Forest (RF) model. In the SVR model, all of the error values are less percent both in X and Y direction. Hence, the predicted values of the model are in good agreement with the data. In this way, the introduced ML model can be effectively applied for calculating the reaction forces and suggesting cutting conditions in order to restrict the developed stress fields in machining.

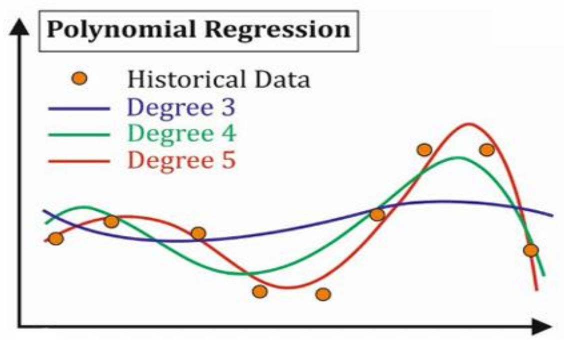


Figure 13.Polynomial Regression Model (Different Degrees)

The impact of the feed rate on the developed cutting forces is demonstrated. Increase in feed rate leads to machining more material, so the chip thickness also grows generating that way higher reaction forces during the milling process. Finally, as radial depth of cut decreases the radial engagement of the cutting tool edge in the workpiece material also diminishes producing smaller chip thickness. Therefore, a reduction in cutting forces takes place as revealed. It is worth mentioning that in situations where the SVR models are employed to evaluate the impact of the examined cutting conditions on the developed milling forces, various conclusion of industrial interest can be generated.

| Sl. No. | Parameters | ANN | SVM | XGBoost | KNN | Random Forest |
|---|---|---|---|---|---|---|
| 1. | R-Squared $R^2$ | 0.9999551260797419 | 0.9984057908862917 | 0.999954751748698 | **0.9999736502911094** | 0.9999527661587125 |
| 2. | MAE | 0.35967455972593904 | 1.402534365167326 | 0.34731724970041666 | 0.24942778366533844 | **0.21969766325404634** |
| 3. | RMSE | 0.4603535220904237 | 2.743892597635629 | 0.4622696320331214 | 0.3527624701883642 | **0.22307052764345311** |
| 4. | MAPE | 8.6545221% | 32.874155% | 8.08250% | 5.722852% | **0.068255%** |

## 4. Results And Discussions

In this work, DoE software Minitab 18 was used to analyse the influence of machining parameters on cutting force. The central composite design method is used to determine the number of experiments to be evaluated for the optimization of the variables and responses. A typical central composite design, named Face Centered Design is used in this analysis. Based on these, 20 trials were generated, and simulations were run in the validated model for each trial.

• The model is validated and the results are given below:

| Feed Rate | Rake Angle | Speed (rpm) | Cutting Force | Cutting Force (Journal) | % Deviation |
|---|---|---|---|---|---|
| 0.1 | 5° | 1600 | 284.1 | 291.2 | 2.4 |
| 0.16 | 0° | 740 | 479.4 | 496.8 | 3.5 |
| 0.15 | 5° | 1150 | 411.34 | 425.22 | 3.26 |

Table: Influence of machining parameters on Cutting Force

Feed rate, depth of cut and temperature have a considerable impact on cutting force. Cutting speed has a less impact on cutting force, possibly because increasing speed does not result in a large temperature change in the quickly moving primary shear zone. When it comes to feed rate and depth of cut, more material comes into contact with the tool in a given amount of time. As a result, it takes greater force to remove the material. Using the desirability function, the optimal combination of machining parameters was identified.

**5.Conclusions**

Orthogonal turning processes aims to validate the experimental results available in the paper with FEM model using ABAQUS. Experiments values of cutting force are valudated using the parameters cutting Speed, Feed rate and temperature. . But due to the disadvantages of the analytical models, further studies were carried out using FEM. A numerical model was developed to simulate the orthogonal turning process and the same is validated with experimental results. To compare and find the optimal machining parameter combination, initially RSM was used for optimization and to investigate the effect of machining parameters.

Further, machine learning technique was used for second validation. Next, ML algorithm was used to predict cutting force for different combinations of parameters. The main conclusions from this study are:

1. Developed ML algorithm is used to predict cutting force is validated with FEM and data available in paper, it was found that the model can be used for effective prediction of the cutting force.
2. In general, it was found that cutting speed has less influence than feed rate, temperature and depth of cut on cutting force (Fc) value. Thus, lower values of feed rate and depth of cut will produce minimum cutting force.
3. Confirmation simulations were run on the validated model and found that results are well acceptable, and the variations are within less than 3.4% only.

This means that the developed model can be used to predict cutting force during orthogonal turning of Ti6Al4V alloys accurately.

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