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ML BASED MODELING AND OPTIMIZATION OF CNC TURNING PROCESS PARAMETERS

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Abstract: In recent times, mechanical and production industries are facing increasing challenges related to the shift towards sustainable manufacturing. In the era of smart manufacturing, production efficiency can be achieved without hampering the quality of the product by optimizing the process parameters. In the present work, the data collected from the machining operations is used for the development of machine learning (ML) based models to test, evaluate and optimize the process parameters of CNC Turning process. Polynomial Regression, Support Vector and Random Forest are applied and the best fit technique is used to develop the model. ML models are used to optimize the process parameters using Teaching and Learning Based Optimization (TLBO)algorithm. The outcome of this work provides tailor-made solutions to enhance the productivity and quality and useful in industries.

Keywords: CNC Turning,Machine learning, TLBO

1. Introduction

Manufacturing industries globally are now focusing on smart manufacturing techniques to improve the production efficiency without hampering the quality of the product. Emerging technologies such as Machine Learning, Internet of Things, Big Data Analytics, CNC Machines and Additive Manufacturing techniques (Z. Zhang et al., 2020; Akhil et al., 2020; Mishra et al., 2020).

Numerous manufacturing industries worldwide are working on smart manufacturing techniques for improving productivity. Various new techniques are being tested for enhancement of productivity according to the industrial revolution, Industry 4.0. Some of these techniques are the Internet of Things (IoT), Machine Learning, Cyber-Physical system, big data, machines with computer controls and sensors and additive manufacturing (Z. Zhang et al., 2020; Akhil et al., 2020; Mishra et al., 2020). By the applications of the above-mentioned techniques, the production level has shown increments. Among all the mentioned techniques, IOT and big data are the most popular techniques Bureaux et al. (2020). The industries 4.0 are working on the information systems based on the sensors attached with the machines (Bricher&M¨uller, 2020).

1.1. Turning: Turning is a machining process in which a cutting tool, typically a non-rotary tool bit, describes a helix tool path by moving more or less linearly while the work piece rotates. Turning can be done manually, in a traditional form of lathe, which frequently requires continuous supervision by the operator, or by using an automated lathe which does not. Today the most common type of such automation is computer numerical control, better known as CNC. (CNC is also commonly used with many other types of machining besides turning.) Turning can be done manually, in a traditional form of lathe, which frequently requires continuous supervision by the operator, or by using an automated lathe which does not. Today the most common type of such automation is computer numerical control, better known as CNC. (CNC is also commonly used with many other types of machining besides turning.) When turning, the work piece (a piece of relatively rigid material such as wood, metal, plastic, or stone) is rotated and a cutting tool is traversed along 1, 2, or 3 axes of motion to produce precise diameters and depths. Turning can be either on the outside of the cylinder or on the inside (also known as boring) to produce tubular components to various geometries. Although now quite rare, early lathes could even be used to produce complex geometric figures, even the platonic solids; although since the advent of CNC it has become unusual to use non-computerized toolpath control for this purpose.

1.2. Machine Learning: Machine Learning (ML) is a branch of artificial intelligence (AI) that enables computers to “self-learn” from training data and improve over time, without being explicitly programmed. Machine learning algorithms are able to detect patterns in data and learn from them, in order to make their own predictions. In short, machine learning algorithms and models learn through experience.Instead of programming machine learning algorithms to perform tasks, you can feed them examples of labelled data (known as training data), which helps them make calculations, process data, and identify patterns automatically.Machine learning can be put to work on massive amounts of data and can perform much more accurately than humans. It can help you save time and money on tasks and analyses, like solving customer pain points to improve customer satisfaction, support ticket automation, and data mining from internal sources and all over the internet.With the help of sample historical data, which is known as training data, machine learning algorithms build a mathematical model that helps in making predictions or decisions without being explicitly programmed. Machine learning brings computer science and statistics together for creating predictive models. Machine learning constructs or uses the algorithms that learn from historical data. The more we will provide the information, the higher will be the performance.

1.3. Genetic Algorithm: The genetic algorithm (GA) works on the evolutionary generational cycle to generate high-quality solutions. These algorithms use different operations that either enhance or replace the population to give an improved fit solution.It basically involves five phases to solve the complex optimization problems Viz. **Initialization,**

Fitness Assignment, Selection, Reproduction and Termination. The flowchart of GA is depicted in fig. 1.

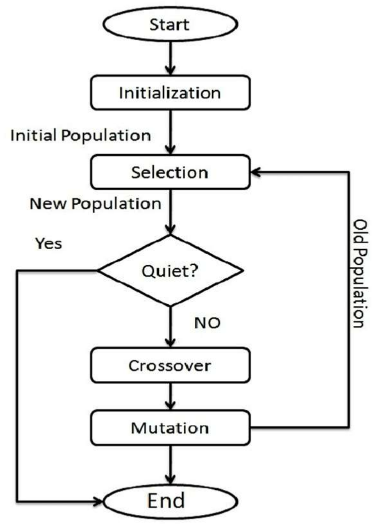


Fig. 1. Flowchart of GA

2. Related work

Nowadays, the research in Machine Learning is flourishing because of large amounts of data that have been accumulated by various industries such as production, health, chemical, manufacturing and information technology (IT). Machine learning plays a vital role for enhancement in demand for artificial intelligence (AI) (Nagargoje et al., 2021). It is a sub branch of AI, which allows the equipment to learn, improve and perform the specific task without disturbing the program.

There are five steps involved in machine learning to solve a problem: problem definition, data collection, modelling, evaluation and result analysis (J. P. Panda & Warrior 2021). There are three broad categories of machine learning algorithms: supervised learning, unsupervised learning, and reinforcement learning. In supervised learning, data are trained for mapping between input and output.

Knowing the ideal output for every sample in the input data acts as a guide for the learning procedure, thus providing supervision. In unsupervised learning, the ideal output is unknown and the model can only learn patterns present in the input data. In reinforcement learning, a predefined signal will be given, depending upon this, the machine will quantify the objectives.

These broad ML approaches can be used for various tasks, such as clustering, dimensionality reduction, surrogate modelling for classification or regression, etc. ML based data-driven surrogate models can act as Digital Twins (DT) for real-life systems and these can be used for system exploration and optimization with a low computational expense. At present, industries are conducting smart machining rather than conventional machining. Because errors are more severe in conventional machining, production is not effective and less efficient. In smart manufacturing, efficient production can be achieved with a stipulated processing time without hampering the quality of the product.

In smart manufacturing, parameters can be optimized in real time through different subsystems and machines like controllers, sensors, systems, and machine tools. Numerous researchers have applied data-driven analysis for machining and production-based problems.

The objective of these studies spans from using data to develop a deeper understanding of the system, to developing ML based models to act as surrogates for the system. Kothari et al. (2018) determined the wear of the cutting tool and its failure using sound signals with the application of Support vector machine (SVM).

The tool wear was predicted accurately through the ML algorithm for different machining conditions. Carrion et al. (2020) predicted the machining quality using ML techniques. The convolution neural network (CNN) was used to predict and monitor the machined surface quality and the results showed that by combining both techniques resulted in 94% accuracy of prediction. Madhusudan et al. (2016) studied the fault diagnosis of face milling using the ML approach.

For the identification of significant parameters, a decision tree algorithm was used. Also, the Naive Bayes model was used for the prediction of fault. It was observed that using the model, the results are predicted with 96.9% accuracy. The ML models developed can be utilized for online monitoring of tool conditions and diagnosis of the fault of the tool used in milling operation. J. Wang et al. (2019) predicted the responses of wire electrical discharge machining (WEDM) through voltage signal using AI technique.

From the analysis, it was found that the unsupervised AI techniques were predicted. Krishnakumar et al. (2018) predicted the tool condition in a high-speed milling process using the ML technique. Four types of ML algorithms are employed, those are artificial neural network (ANN), decision trees, naive Bayes, and SVM. The SVM was found to be the most efficient method to predict the tool condition compared to other techniques. Q. Zhang et al. (2020) predicted the output responses in laser machining using deep multi-task learning. In this experiment, it was observed that Alex Net with multi-task learning was found to be better than deeper models. J. Wang et al. (2020) detected the geometrical defects in WEDM using a physics-guided ANN model.

The inconsistencies in the model were eliminated using a physics guided loss function, from the analysis it was observed that the predicted results matched well with the experimental results with 80% accuracy. Cho et al. (2005) detected the tool breakage in a milling operation using a support vector-based machine learning approach. From the experimental outcomes, it was confirmed that with the said technique, the machine downtime and cost of production can be effectively reduced compared to other techniques. P. Wang et al. (2019) predicted the tool condition through the data-driven hybrid ML approach during milling of H13 steel and Inconel 718. From the results, it was found both the tool wear and surface roughness were predicted effectively with an accuracy of 85% and 90%. Liu et al. (2020) predicted the specific cutting energy with a hybrid approach of integrated ML technique. Both data-driven ML and process mechanics have been hybridized to predict the response. The results are well predicted and the authors claimed that the above-said model can be implemented in other cutting processes.

Vol. 21, No. 1, (2024)
ISSN: 1005-0930

Chiu & Lee (2017) predicted the machining accuracy and surface quality using a data-driven approach by (Adaptive Neuro-Fuzzy Interface System) ANFIS model. From the simulation and experimental results, it was found that results can be effectively predicted through the data-driven model for better quality and productivity. McLeay et al.McLeay et al. (2020) detected the fault during the machining process using an unsupervised ML approach.

Through the PCA plot, the fault conditions are observed. Parwal& Rout (2021) used the machine learning-based approach to predict the tool wear during the machining operation. Various models are employed using logistic regression. The model was found to be good and results are interpreted effectively. And the results are suitable for industrial application. Gouarir et al. (2018) predicted the tool wear through the machine learning techniques. From the results, it was confirmed that the tool wear was predicted effectively with machine learning techniques and the accuracy was 90%. Wu et al. (2017) compared the tool wear prediction results through different ML techniques.

Three types of algorithms are used like feed-forward back propagation (FFBP) based ANNs, random forest (RF) and support vector regression (SVR). Better results are predicted using the RF algorithm. Fang et al. (2016) used a new artificial intelligence approach for the prediction of machined surface roughness in metal machining. ANN model was implemented. From the ANN model, it was observed that the machined surface roughness can be effectively predicted through the ANN model. Ulas et al. (2020) predicted the surface roughness of the machined surface of Aluminium alloy during WEDM with different machine learning algorithms.

Four types of machine learning algorithms are applied such as ELM, W-ELM, SVR, and Q-SVR. Among four algorithms, weighted extreme learning machines (WELM) performed better. Bustillo et al. (2021) predicted the flatness deviation considering the wear of the face mill cutter teeth using a machine learning-based algorithm. Four different types of machine learning techniques were proposed, out of which, Random forest ensembles combined with the Synthetic Minority oversampling technique performed better. Patange&Jegadeeshwaran (2021) predicted the health of a vibration-based multi-point tool insert on a vertical machine centre using a machine learning approach. A tree-based algorithm was proposed by the authors. Various treebased algorithms are used, out of which, the J48 decision tree-based algorithm was 3 found to be the effective one. Oleaga et al. (2018) predicted the chatter in heavy-duty milling operation using machine learning techniques.

Different machine learning models are used out of which, random forest performed better. And the authors concluded that with the use of machine learning techniques, dynamic machining performance can be enhanced in real working conditions. Peng et al. (2019) predicted the cutting forces with consideration of the tool wear using machine learning methods.

Two models are used one is conventional linear regression and the other is a hybrid model with machine learning. From the results, it was observed that the hybrid model with machine learning performed better. Mohanraj et al. (2021) developed a tool condition monitoring system at the end milling process using wavelet features and statistical features-based machine learning approach.

Vol. 21, No. 1, (2024)
ISSN: 1005-0930

Four different types of machine learning techniques are used to predict the flank wear like SVM, K-nearest neighbour (KNN), knowledge based (KB), decision tree, and MLP, and among all, SVM and DT performed better. Sanchez et al. (2018) predicted the thickness change of machined parts during WEDM machining using machine learning techniques. Various models are used to predict the results.

Among various models, a first convolutional layer with two gated recurrent units outperformed the other models. They also concluded that with the large data set, better results can be predicted. Shen et al. (2020) predicted the tool wear size in multi-cutting conditions using advanced machine learning techniques. Different models are used to predict the tool wear and the results are compared with the experimental results. It was observed that there was a good agreement between predicted and experimental results. Moreover, the authors studied that machine learning techniques can be used to predict the other machining responses.

Shastri et al. (2021) optimized the process parameters in the machining of Titanium alloy in an MQL environment using an artificial intelligence-based algorithm. From the experimental results, it was observed that better results in terms of cutting force, tool wear, tool-chip contact length, and surface roughness were obtained using artificial intelligence-based optimization compared to PSO and the experimental approach. Cheng et al. (2020) predicted the tool wear based on machine learning during the turning of high-strength steel.

Two prediction models are used one is grid search algorithm-based support vector and the other is genetic algorithm-based support vector regression. From the results, it was found that with the tool wear, the stages of tool wear in a complete cycle can be easily predicted through machine learning techniques.

Moreover, they suggested that through the machine learning method, tool wear monitoring can be made online. Elsheikh et al. (2021) predicted the residual stress in turning of Inconel-718 using fine-tuned AI model using pigeon optimizer. Two models were incorporated like hybrid ML model and traditional ANN model. The traditional ANN was incorporated with three optimization techniques, those are bio inspired optimization, pigeon and Particle swarm optimization. The prediction accuracy of various models was examined through statistical measures. The traditional ANN was out performed by both ANN-PSO and ANN-PAO.

Jankovic et al. (2018) compared different machine learning methods for cutting parameter prediction in a high-speed turning process. Three types of ML techniques are compared i.e., SVR, Polynomial regression, and ANN.

Cutting force, roughness, and machining time were the output responses. Better results in terms of cutting force and roughness were achieved with polynomial regression. Better machining time was predicted through ANN. The author also observed that for better prediction of results, more data set are required. Cica et al. (2020) predicted various machining responses under different cooling conditions in sustainable machining of 1045 steel using machine learning techniques. From the results, they revealed that an acceptable range of results can be predicted by using machine learning techniques 4 without conducting actual experiments. So, both time and money can be saved by

Vol. 21, No. 1, (2024)
ISSN: 1005-0930

using machine learning techniques. They also revealed that if a wide range of machining conditions will be adopted, better results can be predicted through this method.

Khoshaim et al. (2021) predicted both mechanical and micro-structural properties of friction stir processed aluminium reinforced material using Grey Wolf optimizer. The input parameters are rotational speed, linear processing speed and number of passes, while the outputs were grain size, aspect ratio, micro-hardness and ultimate tensile strength.

The prediction accuracy of developed hybrid model was found to be more accurate compared to standalone model. Zhao et al. (2020) predicted the specific energy consumption of machine tool based on tool wear in a dry milling operation. Three power characteristics are chosen like, standby power, cutting material power and no-load power. Three responses are chosen spindle speed, MRR and tool wear. Both the process parameters and tool conditions are optimized for the reduction in energy consumption of machine tool.

Rasovi&39 (2021) recommended the layer thickness in a powder based additive manufacturing using multi attribute decision support. Many attributes are responsible for the product quality. But author has chosen two criteria one is strength and other is surface roughness. The most suitable layer thickness was proposed by three techniques called weighted features, DFAM knowledge and multiple attributes. Kahya et al. (2021) performed the precision and energy efficient machining of Ti6Al4V alloy on a turn mill machine tool. Three operations are conducted like face turning, rough flank milling and finish milling. Three responses are analysed known as specific cutting energy, roughness and material removal rate. Different angle of inclinations (both lead and tilt) was analysed on the response.

The optimization technique employed was Particle swarm optimization. From the experimental outcomes, it was found that both lead and tilt angle influenced surface roughness effectively. Guo et al. (2021) combined two methods DPCA and IMODE to analyse the effect o9f input variables on the gear quality in a hobbling process. The simulation of gear hobbling data was done and it was compared with NSGA, NSGAII and MODE.

From the outcomes it was found that the proposed algorithm was very effective regarding diversity and optimization ability. Ruiz et al. (2020) predicted the tensile strength of the steel rods by machine learning algorithms those are manufactured in an electric arc furnace. Various ML algorithms are proposed like multiple linear regressions, K-Nearest Neighbors, Classification and Regression Tree, Random forest, Ad boost gradient boost algorithms and ANN. Better results are predicted through fine-tuned random forest. And chemical variables are observed to be the most important variable affecting the material strength.

Tian et al. (2020) optimized the cutting parameters and processing sequence to minimize carbon emissions and process time in a CNC machine using an integrated multi objective optimization technique.

The modeling of process parameters is done using NAGS-II technique. From the results, it was found using integrated multi objective optimization technique, both processing time and carbon emission can be minimized effectively. Saida et al. (2019) used response surface methodology for

Vol. 21, No. 1, (2024)
ISSN: 1005-0930

modelling the output machining responses and optimized the input parameters using a desirability function approach. Jumared et al. (2019) used a similar approach as of Saida et al. (2019) for modelling and optimization of the machining process parameters in ultra-high precision machining of optical lenses. Cagnino et al.Caggiano et al. (2018) optimized the tool life exploitation during CFRP composite drilling in aeronautical assembly using ML techniques. From the experimental outcomes, it was found that both fractal and statistical analysis can predict better results. Shukla & Priyadarshini (2019) applied ML techniques for optimization in WEDM of Haste alloy C-276.

Various techniques have been applied to different machining processes and in this work, CNC Turning process is considered and was carried out by selecting the work piece material and suitable tool. Experimentation was carried out and machine learning dataset was developed based on the experimental data. A machine learning technique, Polynomial regression is applied to obtain ML models for the output parameters. These ML models are considered for optimization process to optimize the process parameters.

2. Methodology

2.1. Experimentation: The work piece considered in this investigation corresponds to a shape of a cylindrical bar having a specification of 75 mm length and 33 mm diameter. The designation of the work piece was Aluminium 7075 grade material. The particular grade was selected because this has got vast applications in particularly tool and manufacturing industries and it has good dimensional stability with good wear and abrasion resistance and shows the chemical composition of the material. Sinumerik 8280 CNC Lathe machine is used to carry out the turning operations. Mitutoyo SJ-210 roughness tester was employed to measure the machined surface roughness. In the current experimental investigation, three input parameters are considered namely, speed (s), feed (f), and depth of cut (d) atfive levels. Speed (500,750,1000,1250 and 1500 RPM), feed (0.5,0.75,1,1.25 and 1.5 mm/rev) and depth of cut (0.1,0.2,0.3,0.4, and 0.5 mm) to analyze different machining characteristics in dry cutting condition. The above parameters and their levels are selected according to the literature review and the tool manufacturer's recommendation and images of experimentation process are displayed in Fig. 2.

Experimental observations were utilized to develop ML dataset. In the tabular representation, each column represents a characteristic attribute and each row represents a specific sample. The first three columns, s, f, d are used as input to the ML models and ML framework is shown in Fig. 3. These represent features that the algorithm uses to model the target output. The next two columns are the outputs of the ML models. The total number of experiments conducted is 25. The input features were normalized to the range -1 to 1 to ensure efficient gradient-based learning. This min-max scaling method for normalization can be defined as follows:

$$\phi_s = \frac{\phi - \phi_{min}}{\phi_{max} - \phi_{min}} \tag{1}$$

Vol. 21, No. 1, (2024)
ISSN: 1005-0930

where, φ_s is the new scaled data, φ is the original cell data, φ_{min} and φ_{max} are the minimum and maximum value in corresponding column. The importance of scaling of input data is to make the learning process numerically stable. The inputs/features of the ML models are s, f and d and the outputs/ levels are *Ra*, *MRR*. We have prepared two train-test datasets (D_1 and D_2) for the development of regression models. The training dataset of D_1 consist of all the data and the traintest dataset D_2 consist of arbitrary testing data from various speed. Those are (500,0.5,0.1), (750, 0.75, 0.2), (1000, 1.25, 0.4), (1250, 1, 0.5), and (1500, 0.5, 0.3) in the order (s, f, d).

2.1. Sinumerik 8280 CNC Lathe machine

2.2. Work piece

2.3. MRR measurement

2.4. Surface Roughness measurement

Fig. 2. Experimentation process

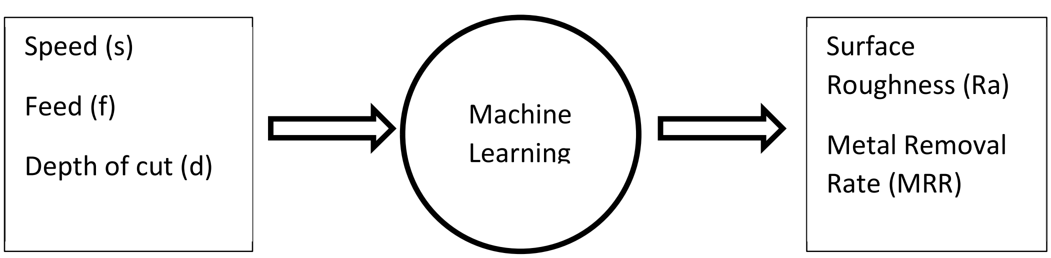


Fig. 3. ML framework used in modeling of machining parameters

In this project work, polynomial regression for predictive modelling of the machining parameters is considered to develop the models for surface roughness and MRR. The predictive performance of the above-mentioned ML algorithm is assessed by using R^2, *MSE* (mean absolute error), and *MAE* (mean absolute error). Those can be defined as follows:

$$R^2 = 1 - \frac{\sum_i (\phi_i - \hat{\phi}_i)^2}{\sum_i (\phi_i - \bar{\phi}_i)^2} \tag{2}$$

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(\phi_i - \hat{\phi}_i)^2 \tag{3}$$

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|\phi_i - \hat{\phi}_i| \tag{4}$$

Polynomial regression is a form of regression analysis in which the relationship betweenthe independent variable *x* and the dependent variable *y* is modeled as an *n*thdegree polynomial in *x*. Polynomial regression fits a nonlinear relationship between the value of *x* and the corresponding conditional mean of *y*, denoted E(*y* |*x*). Although *polynomial regression* fits a nonlinear model to the data, as a statistical estimation problem it is linear, in the sense that the regression function E(*y* | *x*) is linear in the unknown parameters that are estimated from the data. For this reason, polynomial regression is considered to be a special case of multiple linear regressions.

$$y=\beta_0+\beta_1x+\varepsilon \tag{5}$$

$$y=\beta_0+\beta_1x+\beta_2x^2+\varepsilon \tag{6}$$

$$y=\beta_0+\beta_1x+\beta_2x^2+\beta_3x^3+\cdots+\beta_nx^n+\varepsilon \tag{7}$$

2.2. Regression analysis on Ra: Polynomial regression is applied to the experimental data of surface roughness and analysis of variance is carried out. The regression coefficients for individual variables and interactions are generated and statistical data is presented in Table 1. It is observed from table 1 that the value of R Square obtained as 0.9916 represents and fits the data 99.16% and the corresponding ML model is formed as given in eq. (8).

Table 1. SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.878585
R Square	0.9916

Vol. 21, No. 1, (2024)
ISSN: 1005-0930

Adjusted R Square	0.595366
Standard Error	0.090127
Observations	25

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	9	0.439842	0.048871	6.7685	0.000655
Residual	16	0.129967	0.008123		
Total	25	0.569809			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	0.234669	0.218555	1.073727	0.297129	-0.2245	0.693836	-0.2245	0.693836
s	0.0002	0.000207	0.96845	0.345653	-0.00023	0.000634	-0.00023	0.000634
f	0.812023	0.206681	3.928876	0.000984	0.377803	1.246243	0.377803	1.246243
d	-0.69577	1.218936	-0.5708	0.575191	-3.25666	1.865118	-3.25666	1.865118
s.f	-0.0002	0.000316	-0.62432	#NUM!	-0.00087	0.000472	-0.00087	0.000472
f.d	-0.68309	0.574285	-1.18946	0.251611	-1.90052	0.53434	-1.90052	0.53434
s.d	9.79E-05	0.000574	0.170409	0.866825	-0.00112	0.001315	-0.00112	0.001315

Vol. 21, No. 1, (2024)
ISSN: 1005-0930

s^2	-2E-07	2.07E-07	-0.96485	0.34898	-6.4E-07	2.39E-07	-6.4E-07	2.39E-07
f^2	0.436199	0.207121	2.106014	0.051347	-0.00288	0.875275	-0.00288	0.875275
d^2	1.905766	1.843581	1.033731	0.316635	-2.00245	5.813983	-2.00245	5.813983

$$Ra = 0.2347 + 0.0002s + 0.813f - 0.06957d - 0.00028fs + 9.8\text{E-}05sd - 0.68309fd - 2\text{E-}07s^2 + 0.4362f^2 + 1.9058d^2 \quad (8)$$

2.3. Regression analysis on MRR: Polynomial regression is applied to the experimental data of MRR and analysis of variance is carried out. The regression coefficients for individual variables as well as for interactions are generated and statistical data is presented in Table 2. It is observed from table 2 that the value of R Square obtained as 0.91 represents and fits the data over 90% and the corresponding ML model is formed as given in eq. (9).

Table 2. SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.953965
R Square	0.910048
Adjusted R Square	0.802573
Standard Error	0.006847
Observations	25

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	9	0.007589	0.000843	20.2342	7.82E-07
Residual	16	0.00075	4.69E-05		

Total	25	0.008339

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	-0.01488	0.007436	-2.00083	0.058504	-0.03034	0.000586	-0.03034	0.000586
s	-7.1E-06	4.54E-06	-1.57579	0.130019	-1.7E-05	2.29E-06	-1.7E-05	2.29E-06
f	0.030141	0.004536	6.645358	1.41E-06	0.020708	0.039573	0.020708	0.039573
d	0.089336	0.011339	7.878619	1.05E-07	0.065755	0.112917	0.065755	0.112917
s.f	-1.2E-05	2.4E-05	-0.48197	#NUM!	-6.2E-05	3.93E-05	-6.2E-05	3.93E-05
f.d	0.116635	0.043629	2.673347	0.016656	0.024146	0.209124	0.024146	0.209124
s.d	1.87E-05	4.36E-05	0.428174	0.674232	-7.4E-05	0.000111	-7.4E-05	0.000111
s^2	-2.3E-08	1.57E-08	-1.47348	0.160024	-5.7E-08	1.02E-08	-5.7E-08	1.02E-08
f^2	0.023587	0.015735	1.499023	0.153339	-0.00977	0.056944	-0.00977	0.056944
d^2	-0.08265	0.140058	-0.59012	0.563354	-0.37956	0.214259	-0.37956	0.214259

$$MRR = -0.0149 - 7.1472E\text{-}06s + 0.8015f + 0.0893d - 1.256E\text{-}05fs + 1.8680E\text{-}05sd + 0.11603fd - 2.32E\text{-}08s^2 + 0.0236f^2 - 0.0827d^2 \quad (9)$$

2.4. Optimization of turning process parameters

Machine Learning models obtained through polynomial regression (eq. 8, 9) have been utilized for the process of optimization using Genetic Algorithm. The input parameters considered are speed, feed and depth of cut and the output parameters considered are Surface Roughness (Ra) and Metal Removal Rate (MRR). The output responses considered are Ra which is to be minimized

Vol. 21, No. 1, (2024)
ISSN: 1005-0930

whereas MRR is to be maximized and conflict exists between the output responses. Therefore, the unconstrained optimization problem is formulated with single objective function as given below:

Minimize, Objective function (Obj.) = (Ra + (-MRR)) (10)

The parameters used in Genetic Algorithm are given in table 3.

Table 3. Genetic Algorithm parameters

S. No.	Name of the parameter	Value
1	Number of chromosomes in population	16
2	Cross-over probability	0.9
3	Cross-over type	Two-point
4	Mutation probability	0.01
5	Total generations	3000

3. Results and discussion

Before applying the Machine learning technique, the ML data set is checked whether it is normally distributed and the normal probability graphs for Ra and MRR are plotted as shown in Fig. 4 and the observations are noted.

a) There are no unusual data points. Usual data can have strong influence on the results.
b) The sample is sufficient to detect among the means.
c) Sample size are at least 15, normality is not an issue.

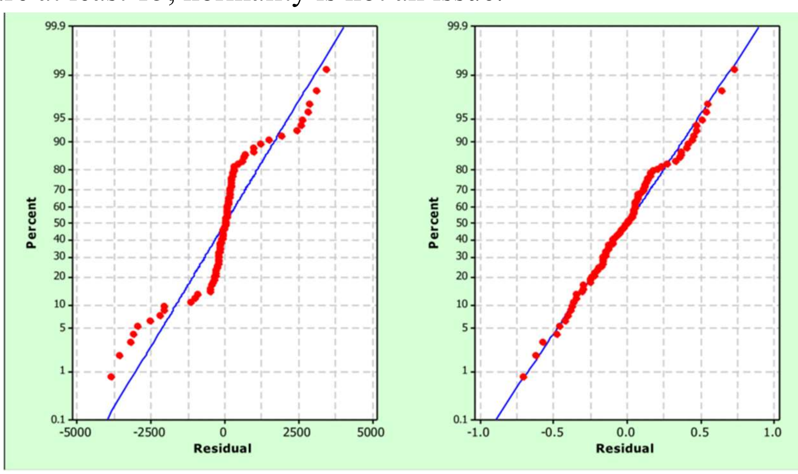


Fig. 4. Normal Probability plots for MRR and Ra

Statistical test parameters are used to validate the obtained models. Three performance parameters for the development and comparison of the predictive capability of the ML models, those are R^2, *MSE* and *MAE* of ML models is presented in the tables 4 and 5. The R^2 values for the two output parameters are found to be more than 95% and the same for train-test dataset which signifies that those models are suitable for predicting the machining parameters. Similar to R^2, *MSE* and *MAE* of predictions obtained as fractions. Therefore, the ML models are validated and suitable for predicting the output responses.

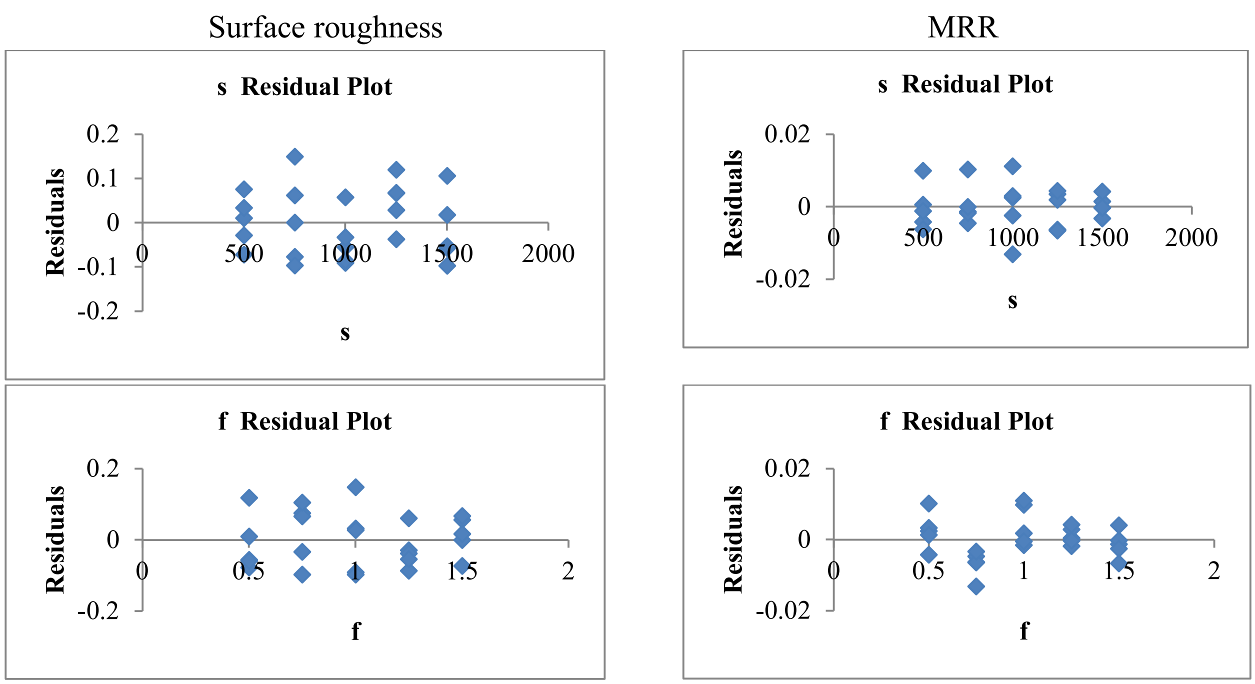
Table 4. ML performance parameters for the train-test dataset D_1

Parameters		R^2	MSE	MAE
Ra	PR	0.9916	0.0002	0.0119
MRR	PR	0.9979	2.85	1.17

Table 5. ML performance parameters for the train-test dataset D_2

Parameters		R^2	MSE	MAE
Ra	PR	0.9974	000000	0.0055
MRR	PR	0.9956	4.6432	1.3173

Further, residual graphs are plotted which display all the residuals are equally distributed as shown in Fig. 5. An ideal residual plot is a residual plot shows the difference between the observed response and the fitted response values. The ideal residual plot, called the null residual plot, shows a random scatter of points forming an approximately constant width band around the identity line.



Vol. 21, No. 1, (2024)
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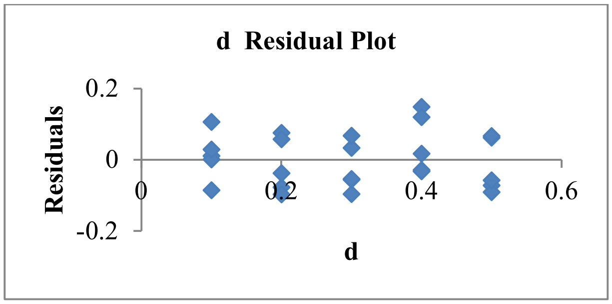

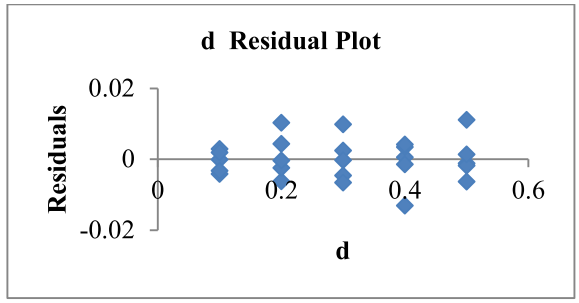

Fig. 5. Residual graphs for output responses

Although the predictive machine learning models using polynomial regression method have been developed, those are characterized by complex non-linear functions, so it is not possible to use traditional optimization methods in conjunction with the ML methods. The correlation between input-output variables has been developed by using polynomial regression and the correlation was used to establish the objective function to be used in the multi-objective optimization. The objective of the multi-objective optimization here is to minimize the *Ra*, and maximize *MRR*. In this work, to solve the optimization problem, popular global optimization technique, Genetic algorithm is used. The objective function is converged at the generation 643 and is constant up to 3000 generations and the convergence graph is plotted and is shown in Fig. 6. A few optimized solutions are considered beyond the generation 643 and a few optimized solutions are presented in the table 6.

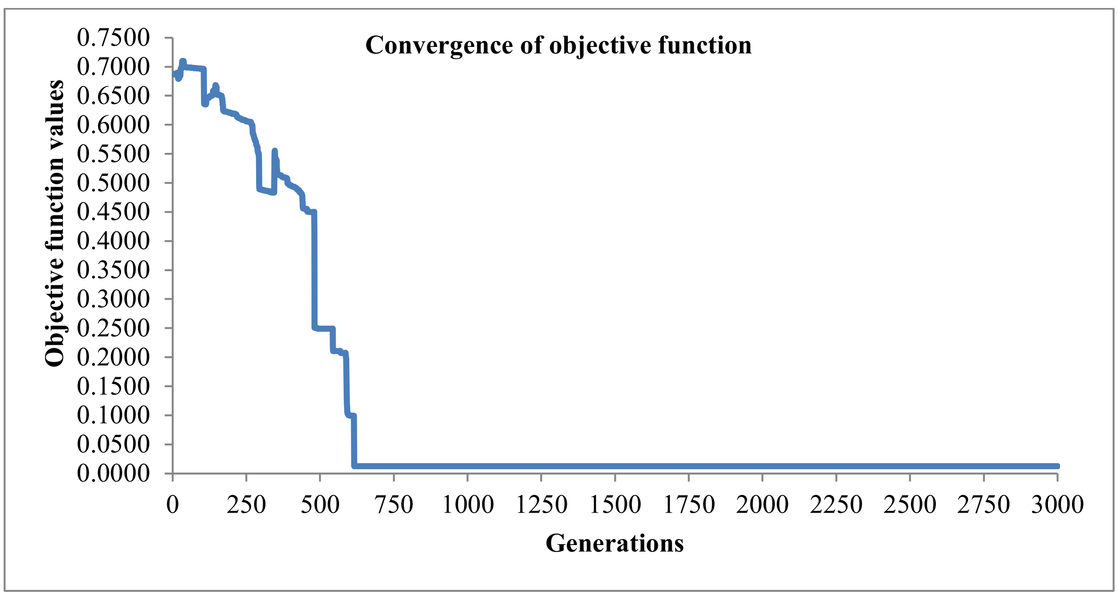

Fig. 6. Convergence graph of objective function

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Table 6. Optimized solutions

S. No.	Generation	Speed (RPM)	Feed (mm/rev)	Depth of cut (mm)	Ra (µm)	MRR (gm/min)
1	750	1247	1.049	0.201	0.3847	0.03820
2	1000	1251	1.051	0.211	0.3827	0.03801
3	1250	1251	1.050	0.2001	0.3798	0.03820
4	1500	1253	1.052	0.1998	0.3839	0.03742
5	1750	1250	1.05	0.21	0.3821	0.03791
6	2000	1255	1.0521	0.212	0.3914	0.03819
7	2250	1252	1.051	0.2199	0.3801	0.03798
8	2500	1251	1.055	0.1989	0.3894	0.03837
9	2750	1253	1.0457	0.213	0.3791	0.03817
10	3000	1251	1.05	0.2	0.3871	0.03798

4. Conclusions

In this work, optimization of parameters CNC turning process is considered. Turning operation was performed through design of experiments on CNC Turning machine. Machine Learning (ML) dataset is prepared based on the observations. Polynomial Regression (PR) technique in ML is used to model the input and output parameters. These ML models are used in the process of optimization. Unconstrained optimization problem is formulated and Genetic Algorithm (GA) is used to optimize the turning process parameters. This methodology is tailor-made frame work and multiple optimized solutions can be obtained. All these solutions are feasible solutions and can be implemented directly on the shop floor. This work is useful in the machining industries to obtain the quality product and to enhance the productivity.

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