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Optimizing CNC Turning Process Parameters Through Machine Learning Modelling

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ABSTRACT

Mechanical and production industries grapple with escalating challenges towards sustainable practices in the age of smart manufacturing. Balancing production efficiency with quality is paramount and achievable through parametric optimization. This work focus on CNC turning data to build the machine learning (ML) model. Polynomial Regression, Support Vector and Random Forest methods are applied and the best fit method is used to develop the model which is usedto optimize the variables using Teaching and Learning Based Optimization (TLBO) algorithm. The outcome of this workprovides tailor-made solutions to enhance the productivity as well as quality and useful in industries.

***Keywords*— CNC Turning, Machine learning, TLBO, Surfaceroughness, MRR**

1. Introduction

Smart manufacturing techniques can increase the productivity without compromising the product's quality. Machine Learning, Internet of Things, Big Data Analytics, CNC Machines and Additive Manufacturing techniques are emerging technologies [1, 2, 3]. The production level has increased with the use of the aforesaid techniques. The industries 4.0 are focusing on the information technologies based on the sensing systems fixed with the machines [4].

CNC turning is a subtractive manufacturing process that utilizes a computer numerically controlled (CNC) lathe to create precise, cylindrical parts. A metal bar stock is securedin a rotating chuck and the CNC program instructs a single- point cutting tool to move along various axes and shaping the work piece by subtracting material until achieving the desired form. This process allows for the creation of complex features like tapered profiles, grooves, and threads,all with high accuracy and repeatability for creating a wide range of components across automotive, aerospace, electronics and other industries.

2. Related work

Machine Learning (ML) falls under the umbrella of Artificial Intelligence (AI), enabling machines to learn, enhance and execute particular tasks and the research is growing vigorously due to the vast amount of data is gettingaccumulated by several industries from production, chemical, health, information technology and

manufacturing. ML has become the pillar for performing various tasks [5]. ML algorithms contain three types: supervised learning, unsupervised learning and reinforcement learning. In the realm of ML, the process typically encompasses stages such as problem definition, data collection, modeling, evaluation, and result interpretation [6]. Within smart manufacturing, productivity goals can be met while maintaining product quality by equipping machine tools with a variety of controllers and sensors, ensuring specified processing times are adhered to.
Researchers used various data-driven approaches and continued their research in determining cutting tool wear using ML techniques [7, 8, 9, 10, 11], machining quality predicted using ML techniques by combining with CNN models [12], fault diagnosis of face milling with ML approach [13], prediction of WEDM responses using unsupervised AI technique [14], predicting tool condition in a high-speed milling process involved employing four ML algorithms: ANN, decision trees, naive Bayes, and SVM. Among these, SVM emerged as the most effective for prediction [15], responses prediction in laser machining using Alex Net with multi-task learning [16], identifying geometric flaws in WEDM involves employing a physics- guided ANN model [17, 18], detection of tool breakage in milling process with SVM method [19], prediction of tool condition with data-driven hybrid ML approach [20], prediction of specific cutting energy using integrated ML technique [21], utilization of the ANFIS model is utilized for forecasting machining accuracy and surface quality [22],fault detection in the machining process using unsupervised ML approach [23], prediction of machined surface roughness with AI approach [24, 25], prediction of residual stresses with AI model [26], optimization of process parameters with AI based algorithms [27] and found the processing sequence to minimize the carbon emissions usingNAGS-II technique [28] is carried out by the researchers. Numerous researchers are actively engaged in leveraging extensive datasets to enhance systems through the application of machine learning and artificial intelligence techniques.

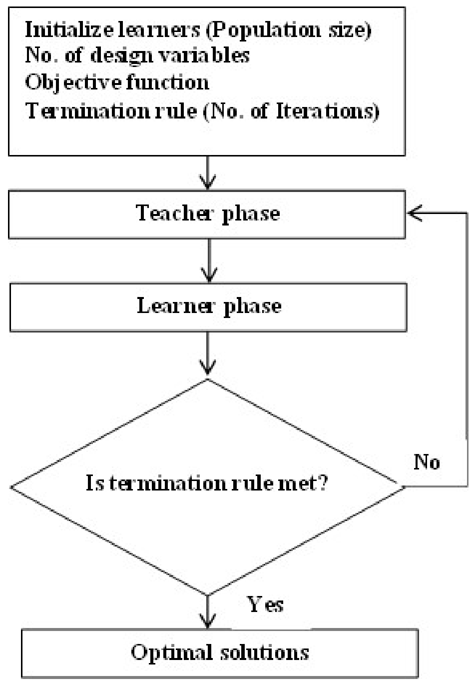
3. Methodology

Various techniques have been applied to different machining processes in the literature and in this work, CNC turning operations are performed on round bar stock of Aluminium 7075 grade with the dimensions, 75x33 mm. This specific grade is chosen due to its widespreadapplications in tool and manufacturing industries, boasting excellent dimensional stability alongside strong wear and abrasion resistance. Experimental observations used as ML dataset to develop models. speed (s), feed (f), depth of cut (d) are considered as input parameters and surface roughness (Ra) and metal removal rate (MRR) as responses. Polynomial regression, support vector regression and random forest techniques from ML are applied to find the best fir technique based on statistical performance. The ML models are employed in the optimization process to refine the process parameters using the teaching-learning basedoptimization (TLBO) algorithm.

Machine learning techniques: Random forest (RF), support vector regression (SVR), and polynomial regression (PR) represent diverse paradigms within the realm of machine learning. Random forest, a powerful ensemble technique, operates by constructing a multitude of decision trees during training and outputs the mean prediction ofindividual trees for regression tasks. In contrast, supportvector regression aims to find the optimal hyper-plane that best separates data points while minimizing error, making it adept at handling both linear and non-linear relationships in data. Polynomial regression, on the other hand, extends linear regression by introducing polynomial terms, effectively capturing non-linearities and interactions, thus offering flexibility in modeling complex relationships between variables. Each method possesses distinct strengths,catering to various data characteristics and problem domains.***Teaching-Learning based optimization (TLBO)***: TLBO [29] is a population-based meta-heuristic algorithm inspired by the teaching-learning process in classrooms. It simulates the collaborative nature of learning, with individuals improving through interactions. TLBO iteratively refines solutions by imitating the teaching process, facilitating effective exploration and exploitation for optimization tasks in diverse domains. The flowchart of TLBO is depicted in Fig. 1, and its popularity stems from its simplicity, straightforward implementation, and versatility in addressing diverse problem domains such as in engineering, operations research, and other fields seeking efficient optimization techniques.

Fig. 1. Flowchart of TLBO

Experimentation and analysis: Experiments are carried out on Sinumerik 8280 CNC Lathe machine for turning operations. Surface roughness of machined surface is measured with Mitutoyo SJ-210 roughness tester and electronic balance for measuring the weight of material removed. Experiments are conducted with orthogonal L25 design matrix and three input variables are considered at five 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) are chosen to analyze output responses, surface roughness and metal removal rate in dry cutting conditions. These parameters and their corresponding levels are determined based on the review of literature and recommendations from tool manufacturer. Images of experimentation process are presented in Fig. 2.
Experimental observations as shown in Table 1 are utilized as ML dataset. The features from ML dataset serve as inputs for the algorithm to predict the target output. The total number of experiments **conducted is 25. The**



dataset isnormalized to ensure efficient grading-based learning and numerical stability during the learning process with the values scaled to the range of -1 to +1 and this is min-max scaling method.
RF, SVR and PR techniques are applied to find the best technique to fit the dataset and find the predictive model. The accuracy of ML models is assessed with the help of R^2, *MSE* (mean squared error), and *MAE* (mean absolute error) and they are mathematically expressed as follows:

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

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

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|\phi_i - \hat{\phi}_i|$$
(3)

ML techniques are implemented using Python and three different split ratios of dataset are considered and they are 80:20, 90:10 and 95:05. Dataset is split into train and test datasets and employed to determine the best fit technique and the statistical performance of these techniques is provided in the Table 2.

2.1. Sinumerik 8280 CNC Lathe machine

2.2. Work piece

2.3. MRR measurement

2.4. Surface Roughness measurement

Fig. 2. Experimentation images and measurement of responses

Table 1. Experimental observations

Experiment no.	Speed (RPM)	Feed (mm/min)	Depth of cut (mm)	Ra (μm)	MRR (gm/min)
1	500	0.50	0.1	0.793	0.773
2	500	0.75	0.2	0.803	0.136
3	500	1.00	0.3	0.962	1.329
4	500	1.25	0.4	1.386	1.445
5	500	1.50	0.5	1.607	0.809
6	750	0.50	0.2	1.995	0.298
7	750	0.75	0.3	1.142	0.187
8	750	1.00	0.4	1.767	0.433
9	750	1.25	0.5	1.827	0.645
10	750	1.50	0.1	1.306	0.345
11	1000	0.50	0.3	1.043	0.224
12	1000	0.75	0.4	1.919	0.251
13	1000	1.00	0.5	1.987	0.524
14	1000	1.25	0.1	1.189	0.287
15	1000	1.50	0.2	1.434	0.401

16	1250	0.50	0.4	2.362	0.237
17	1250	0.75	0.5	2.301	0.282
18	1250	1.00	0.1	1.886	0.161
19	1250	1.25	0.2	1.959	0.265
20	1250	1.50	0.3	0.997	0.422
21	1500	0.50	0.5	1.978	0.283
22	1500	0.75	0.1	1.862	0.675
23	1500	1.00	0.2	1.895	0.218
24	1500	1.25	0.3	2.956	0.344
25	1500	1.50	0.4	2.989	0.554

Table 2. Statistical performance of ML techniques considered

Method	Split ratio of the dataset 80:20					
	MSE	**MAE**	**R^2**	**MSE**	**MAE**	**R^2**
PR	**0.3506**	**0.4560**	**0.2958**	**0.1152**	**0.2144**	**-1.6081**
SVR	**0.3581**	**0.5595**	**0.2806**	**0.0173**	**0.1149**	**0.6064**
RF	**0.3107**	**0.4648**	**0.3758**	**0.0158**	**0.1135**	**0.6403**
Method	Split ratio of the dataset 90:10					
	MSE	**MAE**	**R^2**	**MSE**	**MAE**	**R^2**
PR	**0.1662**	**0.2684**	**0.5806**	**0.1484**	**0.2434**	**-2.4318**
SVR	**0.2171**	**0.4654**	**0.4523**	**0.0264**	**0.1447**	**0.3889**
RF	**0.1366**	**0.3100**	**0.6553**	**0.0034**	**0.0553**	**0.9213**
Method	Split ratio of the dataset 95:05					
	MSE	**MAE**	**R^2**	**MSE**	**MAE**	**R^2**
PR	**0.0027**	**0.0519**	**0.9516**	**0.0011**	**0.0325**	**0.9677**
SVR	**0.2418**	**0.4895**	**-3.3059**	**0.0127**	**0.0973**	**0.6134**
RF	**0.0366**	**0.1912**	**0.3483**	**0.0085**	**0.0925**	**0.7391**

It is observed from Table 2 that PR is best suited technique for the given dataset as R-squared values for Ra and MRR are found to be more than 95% and the errors are also found to be minimum. Therefore, PR with split ratio 95:05 is applied to develop the ML models**.**

*Regression analysis***:** PR is applied to the experimental data on output responses and the analysis is carried out. The regression coefficients for individual variables and interactions are generated. It is observed from table 2 thatthe value of R-Square obtained as 0.9516 for *Ra* and 0.9677 for *MRR* which represents and fits the data 95.16% and 96.77% respectively and the corresponding ML models for responses are formed as given in (4) and (5).

$$Ra = 0.3799 + 0.00039s - 0.1951f - 1.4964d + 0.0000001185s^2 + 0.00053sf + 0.00005631sd - 0.318f^2 + 1.4715fd + 2.7384d^2 \quad (4)$$

$$MRR = 1.3394 - 0.002723s + 0.5165f + 0.8162d + 0.0000014s^2 - 0.00024sf - 0.00076sd - 0.1129f^2 + 0.4743fd - 0.2731d^2 \quad (5)$$

Optimization of turning process parameters*:* Equations (4) and (5) are utilized for the process of optimization using TLBO which require only two parameters, namely, population size and number of iterations. TLBO is implemented in Python code with population size as 50 and number of iterations as 100. The output responses considered are Ra which is to be minimized whereas MRRis to be maximized and a conflict exists between the output responses. Therefore, the optimization problems are formulated as single response as well as multi-response optimization problems.

4. Results and discussion

Before applying the ML techniques, the data set ischecked whether it is normally distributed and the normal probability graphs for Ra and MRR are plotted and aredepicted in Fig. 3.

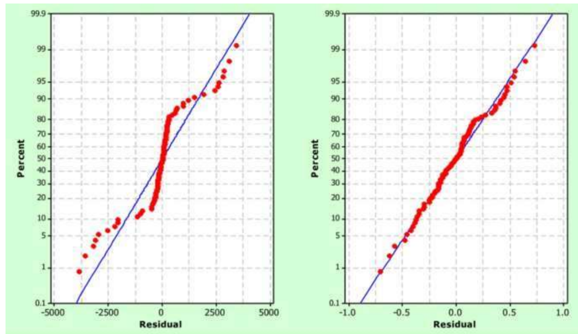


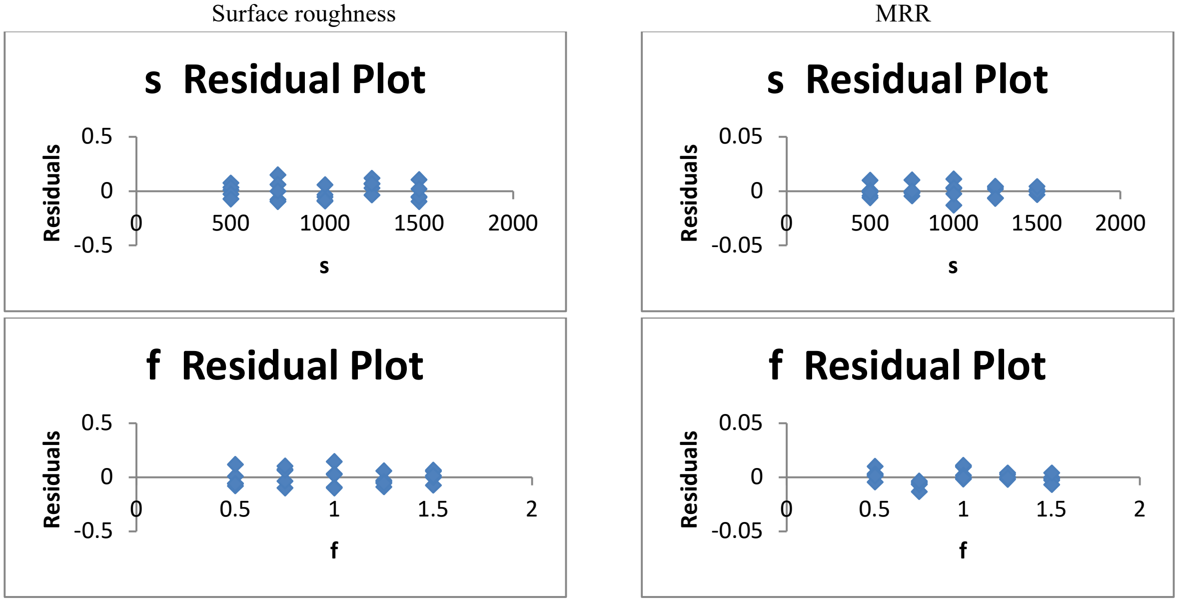
Fig. 3. Normal Probability plots for MRR and Ra

Statistical test parameters are used to validate the obtained models. Three performance metrics are employed to develop and compare the predictive capacity of the ML models as given in table 2. R^2 values for the two output parameters are found to be more than 95% for the split of dataset at 95:05 signifies that those models are suitable for predicting the machining parameters. Therefore, the ML models are validated and suitable for predicting the output responses. Further, residual graphs are plotted which displayall the residuals are equally distributed as shown in Fig. 4. Mathematical relationships between input parameters and responses are established by applying PR and ML models utilized as the objective functions in the optimization process. Optimization of output responses *Ra* and *MRR* is carried out as single objective optimization problems. The corresponding convergence plots are drawn and presented inFig. 5 and 6.

It is observed from Fig. 5 and 6 that output responses *Ra* and *MRR* have converged at 45th iteration and 38th iteration respectively. Further, both the responses, Ra and MRR are considered as multi-response optimization problem with equal weights and convergence plot is drawn and presented in Fig. 7. It is noted that the objective function converges by 9th iteration and is constant up to 100 iterations. A few optimized solutions of multi-response optimization are presented in the Table 6.

Surface roughness

MRR



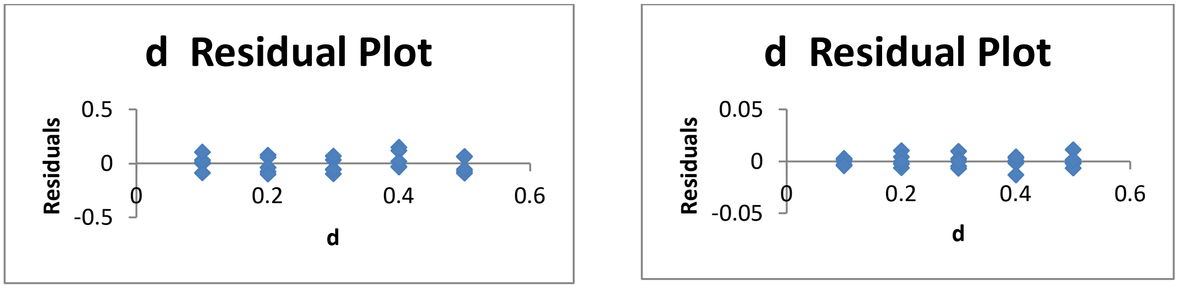


Fig. 4. Residual graphs for output responses

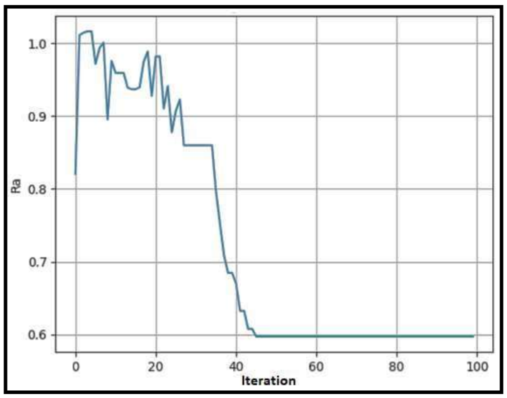


Fig. 5. Convergence plot of Ra

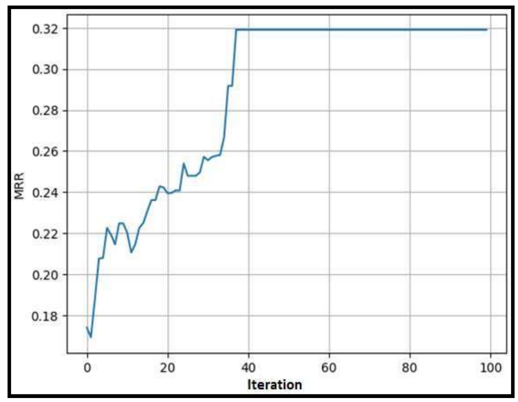


Fig. 6. Convergence plot of MRR

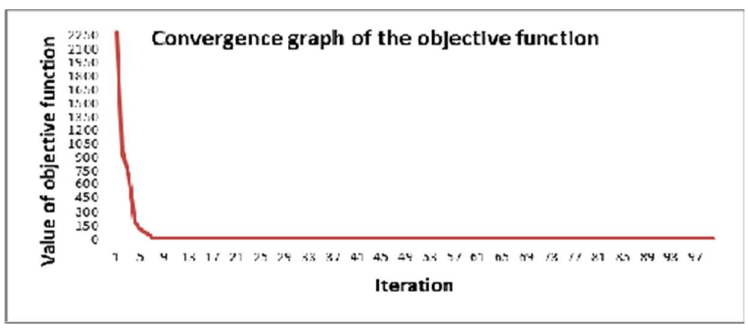


Fig. 7. Convergence plot of multi-response objective function

Table 6. A few optimized solutions

S. No.	Speed (RPM)	Feed (mm/rev)	Depth of cut (mm)	Ra (µm)	MRR (gm/min)
1	500	0.5	0.1	1.016	0.319
2	500	0.5	0.5	1.392	0.404
3	1500	1.5	0.1	2.015	0.404
4	1500	0.5	0.5	2.302	0.561
5	1500	1.5	0.5	3.002	0.764

5. Conclusion

This study focuses on employing machine learning (ML)for modeling and optimizing parameters in CNC turning process. Three techniques—PR, SVR and RF are tested to determine the most suitable. PR emerges as the optimalchoice and it is then utilized to model input and output parameters, while ML aids optimization using

Teaching- Learning-Based Optimization (TLBO). Surface roughness and metal removal rate are individually optimized, as well as a combined objective function. This framework is customizable, generating multiple feasible solutions applicable to the shop floor. Furthermore, it may be adaptable to various aluminum alloys, offering significant potential for enhancing the product quality of the machiningindustry.

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