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Performance Enhancement of CNC Milling Process using Different Machine Learning Techniques

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Abstract

Towards the requirement of technological development, it is necessary to optimize the machining parameters in the manufacturing process. Nowadays machine learning algorithms have proven their potential towards a performance enhancement process compared to conventional methods. In the present study, the different machine learning methods such as Linear Regression, Decision tree algorithm, ANN are used for prediction of process parameters of CNC milling process. Performance Enhancement can be achieved through predicting the proper combination of cutting speed, feed and depth of cut with the objectives of Minimum machining time, maximum material removal rate, minimum surface roughness and maximum tool life. Mathematical models are developed using a regression tool in MINITAB. Modelling of machine learning algorithms is done using python codes. Comparison of different machine learning algorithms are done to select the best optimization tool for this process enhancement procedure.

Keywords: *ANN, KNN, Linear Regression*

1.0 Introduction

Milling is one of the key machining processes in manufacturing industries. Introduction of High Speed Machining (HSM) increases the application of the milling process in the manufacturing industry. In olden days selection of machining parameters are done using handbooks or based on the experience of operators. Performance enhancement is not possible with the above procedure due to increase in complexity of machining shapes and non linearity of optimization problem. To overcome the above issues, the different machine learning techniques are proposed in this paper for the selection of process parameters of the machining process.

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In [1], authors optimized the process parameters such as depth of cut, feed and cutting speed of milling of Al5059/SiC/MoS_2. Regression and ANN are used for optimization and ANN gives better results compared to regression. Feed rate is found as an influential process parameter using ANOVA. In this paper[2], prediction of surface roughness of high speed milling and process parameter optimization is studied and experimented to achieve minimum production time and better surface quality. Non dominated Sorting Genetic Algorithm (NSGA-II) is used to optimize the multi objective optimization problem.

The aim of this study[3] is to optimize the flat end milling process using single performance Taguchi analysis and multi performance Taguchi Gray relational analysis (TGRA). The results are compared to a multi-objective genetic algorithm. In this paper[4], end milling operation of hardened custom 465

steel with multi objectives such as cutting force, temperature, surface roughness and material removal rate are optimized using Taguchi matrix with Gray relational analysis. In this study[5], montmorillonite clay (MMT) is chosen as material because of its natural occurrence, inexpensive and eco-friendly. The three levels of Box Behnken experimental design is utilized to optimize the process parameters such as feed rate, cutting speed and depth of cut and also the concentration of the cutting fluid. ANOVA is used to analyze the influence of individual parameters as well as combination of parameters. Verification of mathematical models is done by getting a higher R square value.

In[6], the authors focused on maximization of the material removal rate of the milling process of thin-walled structures with respect to vibration and stability constraints. Risk of local minimum convergence is avoided using resampling strategy. Common optimization strategy is used for optimization in this paper. In[7], the authors discussed the response surface methodology based cutting force optimization for the milling process of M200 TS. The magnitude variation in the cutting force plays a very important role in the overall machining process optimization. High precision and accuracy in cutting force are achieved by the piezoelectric force sensors.

In this paper[8], multivariate technique coupled with Response surface methodology is used as a tool for modelling and optimization of the process parameters of end milling operation in duplex stainless steel. In this paper[9], recorded data of controller and sensor signals are used to build a dexal based mechanistic cutting force model. Bayesian technique and dynamic time warping are combined to predict the variables. Better observations are made between simulation and experimentation variables. In[10], single and multi-objective optimization of the performance characteristics are performed to identify the optimum combination of decision variables such as cutting speed, feed rate and radial depth of cut of the face milling of Ti6A14V. ANOVA is used to find the influential input variable on performance characteristics and Regression is used for mathematical modelling.

In[11], the objective of this paper is to increase machining efficiency and reduce the surface defects for high-speed dry (HSD) milling. Minimum surface defects are achieved using GA-BP which is the hybrid algorithm of Genetic algorithm and Neural network, NSGA-II (Non-dominated Sorting Genetic Algorithm-II) which is the pareto optimal based Genetic algorithm. In[12], authors developed the algorithm for increasing efficiency and reducing the cost for micro-milling process by analyzing the parameters such as cutting force, tool deflection and surface roughness. The developed algorithm accuracy is verified with the case study of micro-milling processes with increased material removal rate and reduced processing time.

In[13], the main focus of the author in this paper and manufacturing industries is to reduce the machining time, so as to reduce the cost without compromising the quality. Simulation based Genetic algorithm is used to optimize the parameters such as speed and feed for milling machines to obtain the minimum machining time. In[14], authors explained the procedure which can be used to find the optimum parameters for any required response value in helical ball end milling process. The process improvement is achieved by setting the optimum values for process parameters. In[15], the statistical optimization of multi response variables is carried out for 5754 aluminum alloy. Materials removal rate and MRR are considered as main objectives in this paper to obtain improvement in machine productivity and surface quality.

In most of the research papers speed, feed and depth of cut are considered as the main process parameters[1,2,3,10] etc for optimization for high speed milling process. There are a number of objectives are considered in milling process optimization such as maximize Material Removal Rate (MRR)[4,6,12,15], minimize surface roughness[2,4,11,15], minimize machining time[2,4,12,13] and optimize cutting force[7]. Different optimization techniques such as Artificial Neural Network (ANN)[1], Genetic Algorithm[13], Non-dominated Sorting Genetic Algorithm (NSGA_II)[2,11], Taguchi Gray Relational Analysis[3,4], Response Survey Methodology[7,8], Bayesian Techniques[9] and hybrid of GA and ANN[11] are used as a tool for performance enhancement. In most of the papers ANOVA[1,5,10] is used to find the influence of process parameters on the performance characteristics.

In this study, all major four objectives are considered and a computerized algorithm is developed to find optimum process parameters to obtain minimum machining time, maximum material removal rate, minimum surface roughness and maximum tool life. Different machine learning techniques are utilized for optimization in this paper.

2.0 Objective

Any optimization problem will comprise a single or more objective function with many constraints. This paper has four objective functions which are Minimum machining time, maximum material removal rate, minimum surface roughness and maximum tool life with respect to machine power and boundary constraints of input parameters.

3.0 Methodology

1. A case study of a specific dimension component is identified for production using a CNC milling machine. Mild steel is chosen as a material for the production. Random selection of different combinations of speed, feed and depth of cut within the available range of input

parameters is done for the machining process.
2. Initial and final weights of the components are found and time taken for machining also observed. Surface roughness is measured using a portable Talysurf machine for face milling and corner milling and surface roughness of slots are measured in surface measuring machine at CMTI.
3. MRR and Tool life are calculated using the following formulas
   MRR = Wi-Wf/ρ*t.
   T = (C/V)1/n
4. Mathematical modelling of objective functions is performed using the regression function MINITAB.
5. Obtained mathematical models are used for optimization. Modelling and training of machine learning algorithms are coded using python.

4.0 Experimental Verification

The above algorithm is verified with experimentation which is carried out in a CNC milling machine at a small scale industry in Penia, Bangalore. The components are machined in Vertical Machining Center (VMC) which is shown in Figure 1. The

Table 1: Observations from facemilling

	Speed (S)	Feed (F)	Depth of cut (DOC)	Time (T)	Surface Roughness (SR)	MRR	Tool life (T)
Unit	(rpm)	(mm/min)	(mm)	(min)	(µm)	(mm^3/sec)	(min)
1	1800	600	0.2	43	3	10	4011
2	1800	600	0.3	30	1.2	20	4018
3	1800	600	0.4	17	0.5	31	4025
4	1800	700	0.2	35	3.5	17	4006
5	1800	700	0.3	22	1.8	28	4013
6	1800	700	0.4	9	0.1	38	4021
7	1800	800	0.2	27	4	24	4002
8	1800	800	0.3	14	2.3	35	4009
9	1800	800	0.4	10	0.6	45	4016
10	1900	600	0.2	52	6.8	4	3218
11	1900	600	0.3	39	5	15	3225
12	1900	600	0.4	26	3.3	25	3232
13	1900	700	0.2	44	7.3	11	3213
14	1900	700	0.3	31	5.6	22	3220
15	1900	700	0.4	18	3.8	32	3227
16	1900	800	0.2	36	7.8	19	3209
17	1900	800	0.3	23	6.1	29	3216
18	1900	800	0.4	10	4.4	39	3223
19	2000	600	0.2	61	10.6	-2	2425
20	2000	600	0.3	48	8.8	9	2432
21	2000	600	0.4	35	7.1	19	2439
22	2000	700	0.2	53	11.1	5	2420
23	2000	700	0.3	40	9.4	16	2427
24	2000	700	0.4	27	7.6	26	2434
25	2000	800	0.2	45	11.6	13	2416
26	2000	800	0.3	32	9.9	23	2423
27	2000	800	0.4	19	8.2	33	2430

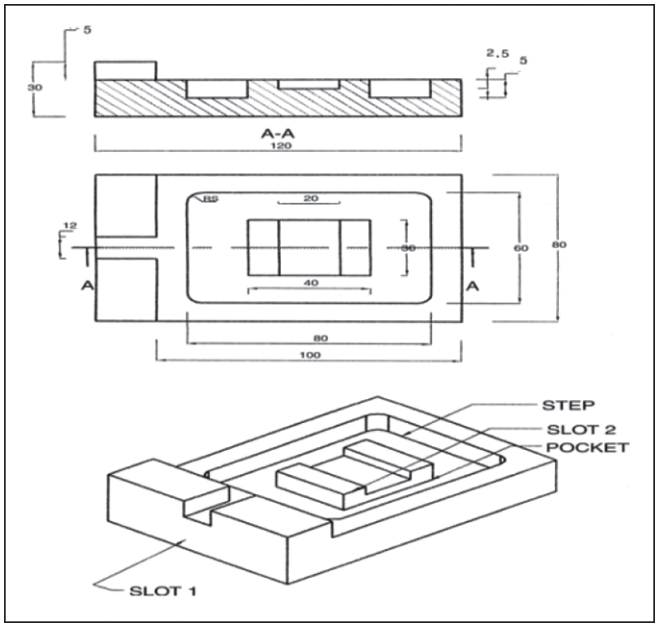


Figure 1: Component

specifications of the machining center and constants used for calculations are tabulated below.

The component is selected which has all four types of milling operation such as face milling, corner milling, slot milling and pocket milling. Mild steel plate is procured as cross section of 125mm*35mm*1000mm and cut in to pieces of cross section of 100mm*80mm*35mm.

4.1 Experimentation

Initially face milling operation is performed with L27 orthogonal array of input variables in the given range and corresponding output variables observed and tabulated in Table 1

4.2 Selection of Algorithm

Machine learning algorithms are selected based on the available data sets. Machine learning algorithms are mainly classified as three types such as supervised and unsupervised algorithms. Supervised algorithms are used for the labelled data (both input and output) and unsupervised algorithms are meant for unlabelled data (only input). Supervised algorithms are further classified into regressor (continuous output) and classifier (discrete output). Experimental data obtained for this study is the labelled data with continuous output values. So the supervised regression algorithms are selected for this study. Linear regression, K-Nearest Neighbor Algorithm (KNN Regressor) and Artificial Neural Network (MLP Regressor) are selected for modelling and predictions.

4.3 Modelling and Analysis

Input parameters such as speed, feed and depth of cut and output parameters such as machining time, surface roughness, MRR and tool life values are given as an input to the machine learning models. There are three machine learning techniques such as Artificial Neural Network (ANN), K Nearest Neighbor Algorithm (KNN) and linear regression that are selected for the modelling and prediction of output parameters for performance enhancement. The input and output parameters given in Table 1 is feeded to the algorithm as an excel sheet. Modelling of algorithms is done using python software. Initially the data set is splitted into 2 sets, one for training and another one is for testing the algorithm. 30% of data is randomly selected for testing and balance 70% of data is selected for modelling. Both input and output values of the training set is feeded to the algorithm for training. After training the model, only the input values are feeded to the model for prediction. Then the predicted values are compared with output values of testing data and the

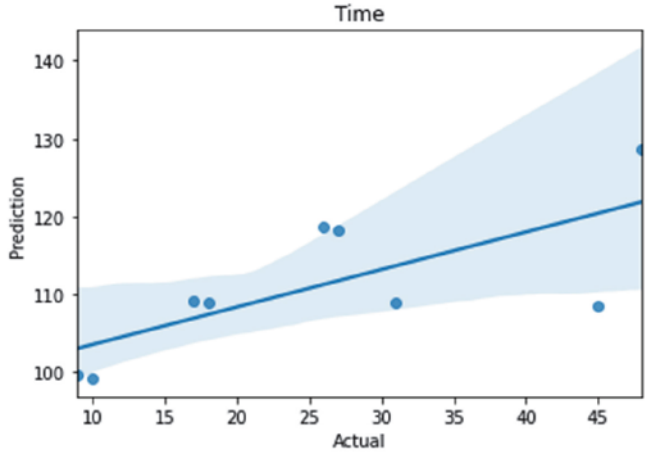


Figure 2: Prediction vs actual time values using ANN

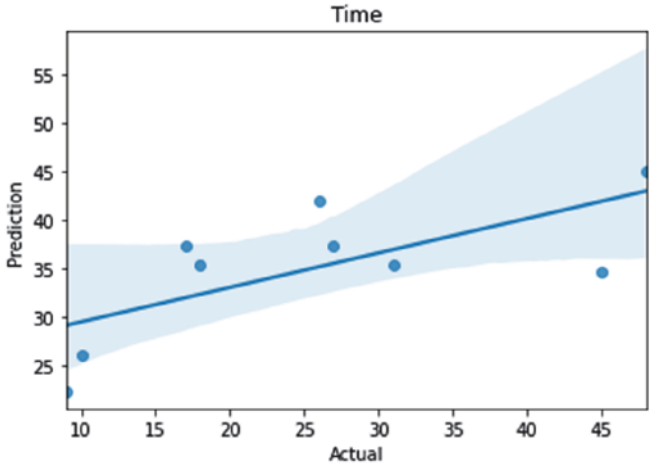


Figure 3: Prediction vs actual time values using KNN

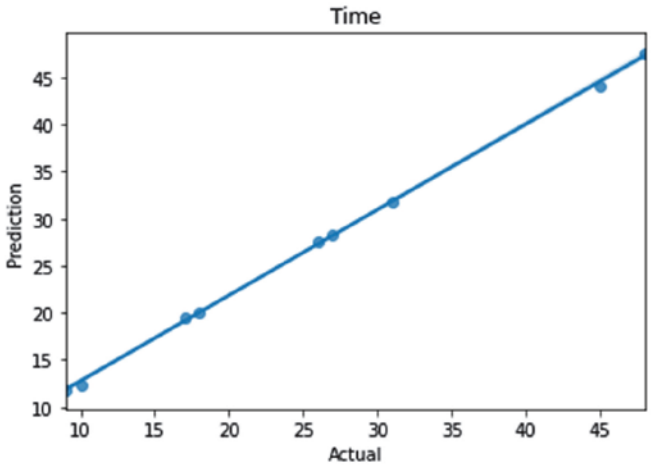


Figure 4: Prediction vs actual time values using linear regression

model is evaluated using the R^2 value of ANOVA. Predicted values each output with actual values in testing data is plotted using different algorithms such as ANN, KNN and linear regression. Prediction of machining time versus actual times values are plotted for all three algorithms which is shown in Figures 2 to 4.

Initially the predictions made using ANN which are shown in Figure 2, in which three predictions are out of fitting region and all others predictions are in acceptable fitting region and its R^2 value is 83.3%. Secondly the predictions are made using KNN, in that only two points are out of fitting range and which has an R^2 value of 87.2% shown in Figure 3. Finally modelling is done using linear regression and predictions are fitted almost exactly on a fitting line which has an R^2 value of 99.7% which is shown in Figure 4. By comparing all the predictions using different machine learning techniques, it is observed that linear regression predictions are better than the other two algorithms.

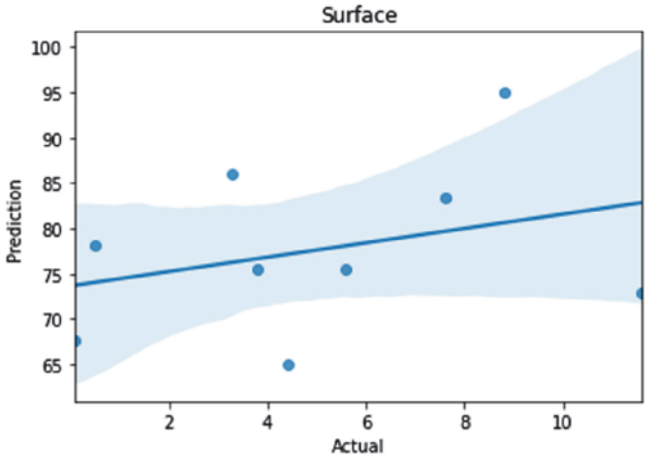


Figure 5: Prediction vs actual surface roughness values using ANN

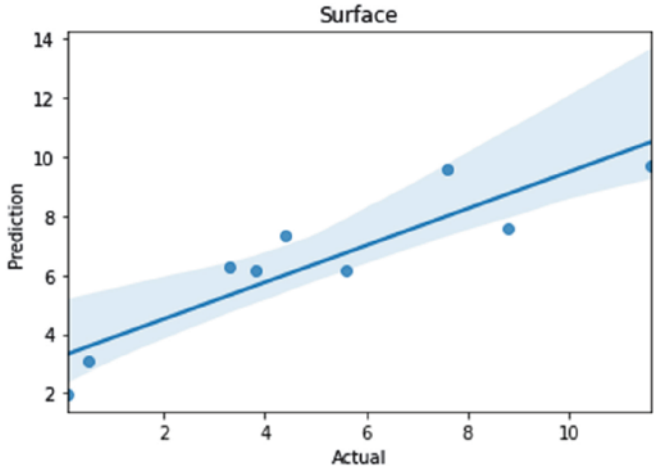


Figure 6: Prediction vs actual surface roughness values using KNN

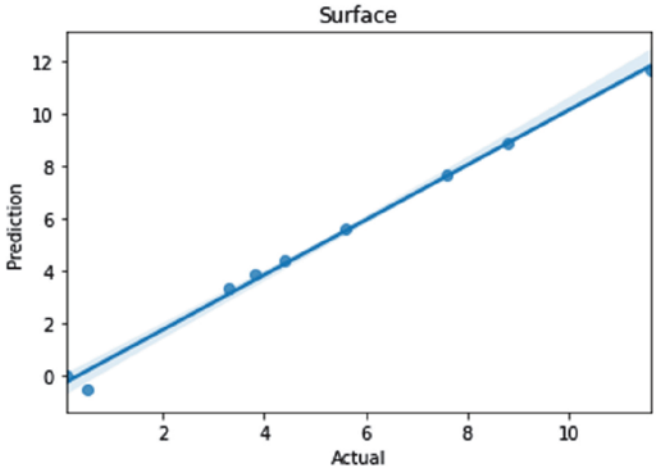


Figure 7: Prediction vs actual surface roughness values using linear regression

Similarly the predictions of surface roughness are made using ANN, KNN and linear regression and plotted against the actual values of surface roughness measured from experiment which is shown in Figures 5 to 7. It is observed from the graph that some predictions made using ANN and KNN are out of fitting region which has an R^2 value of 69% and 90.3%. But predictions of linear regression are exactly fitting with the fitting line which has an R^2 value of 99.7%. Again it is proven that linear regression predictions are better than the other two algorithms.

From Figures 8 to 10, prediction values of Material Removal Rate are compared to the actual values of testing data and plotted. By observing all three graphs of ANN, KNN and linear regression, linear regression predictions are exactly fitting with the fitting line or the model. Predictions of linear regression model has an R^2 value of 100% where ANN and KNN have 83.1% and 93% respectively.

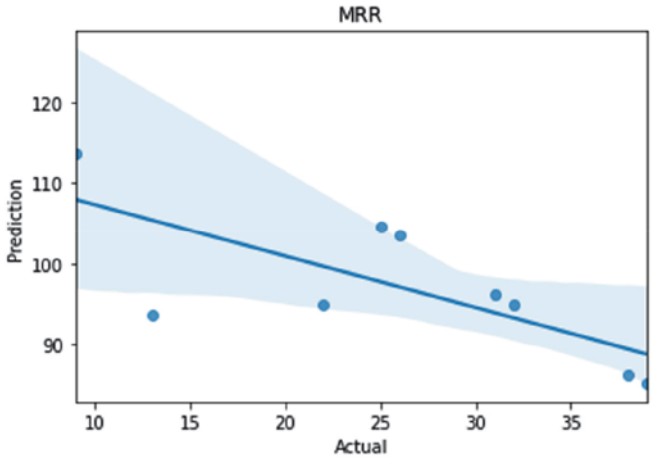


Figure 8: Prediction vs actual MRR values using ANN

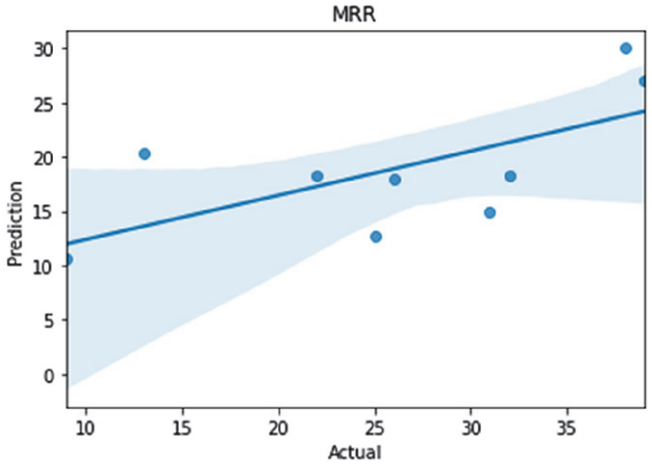


Figure 9: Prediction vs actual MRR values using KNN

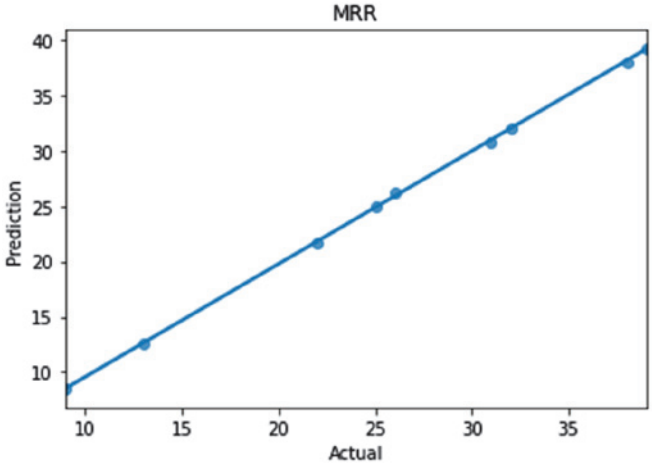


Figure 10: Prediction vs MRR values using linear regression

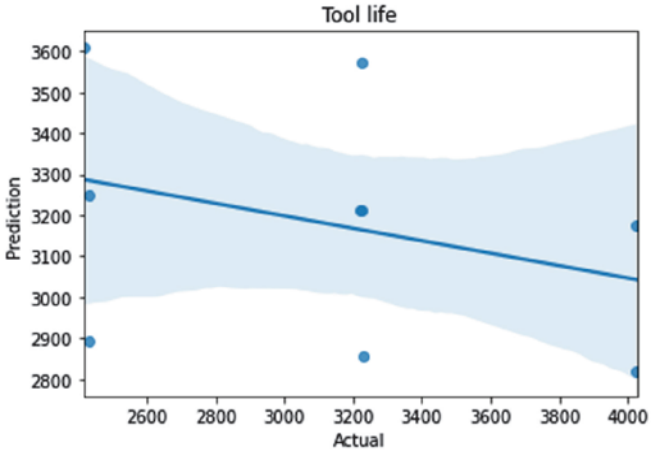


Figure 11: Prediction vs actual tool life values using ANN

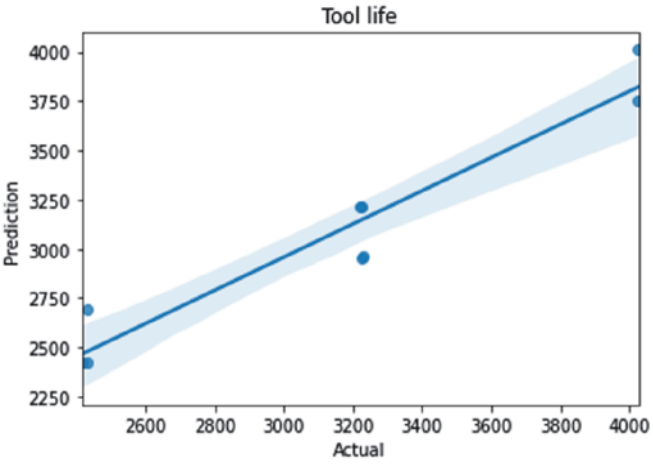


Figure 12: Prediction vs actual tool life values using KNN

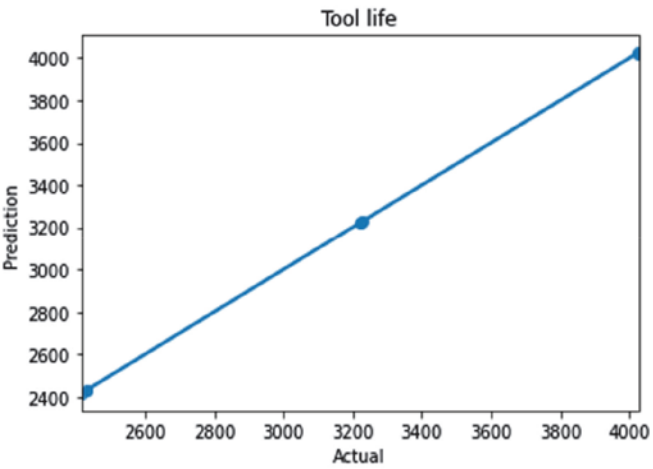


Figure 13: Prediction vs tool life values using linear regression

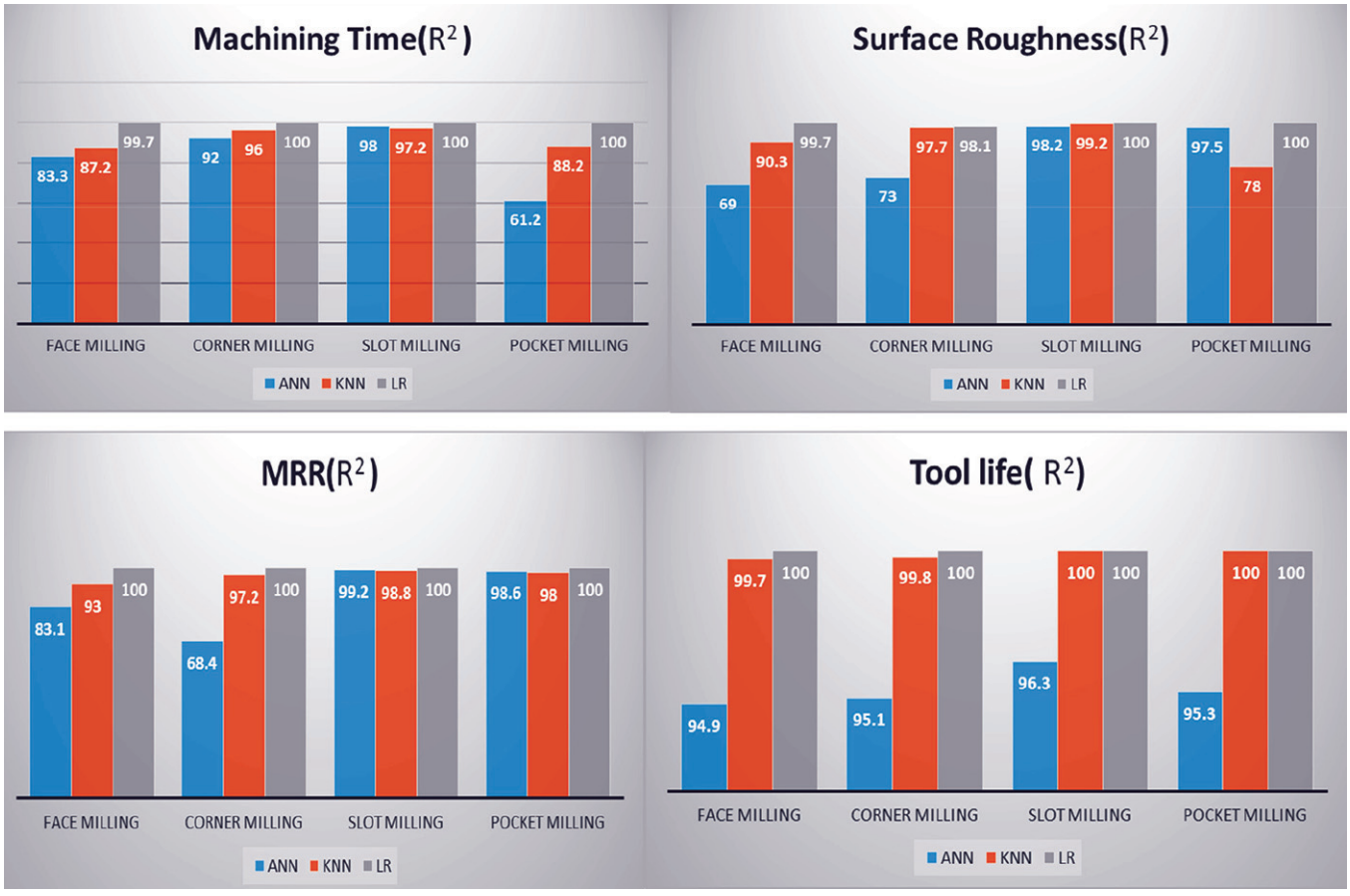


Figure 14: Comparison of R^2 value of models using ANN, KNN and LR

Table 2: Performance comparison of different Algorithms

	Machining	R^2 Value(%)											
		Time			Surface Roughness			MRR			Tool life		
		ANN	KNN	LR	ANN	KNN	LR	ANN	KNN	LR	ANN	KNN	LR
1	Face Milling	83.3	87.2	99.7	69	90.3	99.7	83.1	93	100	94.9	99.7	100
2	CornerMilling	92	96	100	73	97.7	98.1	68.4	97.2	100	95.1	99.8	100
3	Slot Milling	98	97.2	100	98.2	99.2	100	99.2	98.8	100	96.3	100	100
4	Pocket Milling	61.2	88.2	100	97.5	78	100	98.6	98	100	95.3	100	100

Tool life predicted using different algorithms are plotted against its actual value of testing data which is shown in Figures 11 to 13. Tool life prediction of linear regression has 100% R^2 value and where ANN and KNN have 94.9% and 99.7%. All the predictions of tool life points are exactly fitting with the model.

Similarly the experimental datas obtained from corner milling , slot milling and pocket milling are used for modelling with ANN, KNN and linear regression. The R^2 value of the models using different algorithms such as ANN, KNN and linear regression for all four objectives are tabulated for entire components operations which is shown in Table 2.

Performance comparison of three algorithms are done using a bar chart which is shown in Figure 14; observations from the charts are the prediction of using linear regression is better than KNN and ANN.

5.0 Conclusions

In this study, a specific mild steel component is selected and four types of milling operations are performed on a CNC milling machine. The experiments are conducted based on an L27 orthogonal array. The process parameters are speed, feed and depth of cut and the major four objectives are minimum machining time, maximum material removal rate, minimum surface roughness and maximum tool life. After conducting the experiment, the obtained datas are utilized to model different machine learning algorithms such as linear regression, KNN and ANN. Then the predictions are analyzed using R^2 values and the major observation is linear regression models are more accurate than other two models. The present work can be extended with different machining operations and for different algorithms.

6.0 References

1. S. Ajith Arul Daniel, R. Pugazhenthi, R. Kumar, S. Vijayananth, (2019): "Multi objective prediction and optimization of control parameters in the milling of aluminium hybrid metal matrix composites using ANN and Taguchi-Grey relational analysis", *Defense Technology* 15 (2019) 545-556.
2. Xuefeng Wu, Xuefeng Yin, (2018): "Surface roughness analysis and parameter optimization of mold steel milling", Procedia CIRP 71 (2018) 317–321
3. Muhammed Muaz, Sounak Kumar Choudhury, (2019): "Experimental investigations and multi-objective optimization of MQL-assisted milling process for finishing of AISI 4340 steel", *Measurement* 138 (2019) 557–569
4. Kanchana J, prasath V, Krishnaraj V, Geetha Priyadharshini, (2019): "Multi response optimization of process parameters using Grey relational analysis for milling of hardened custom 465 steel", Procedia Manufacturing 30 (2019) 451–458.
5. Laura Peña-Parása, Demófilo Maldonado-Cortésa, Martha Rodríguez-Villalobosb, Angel G. Romero-Cantúa, Oscar E. Montemayora, Mónica Herreraa, Gabriela Troussellea, Jaime Gonzálezа, Walter Huglerc, (2019): "Optimization of milling parameters of 1018 steel and nanoparticle additive concentration in cutting fluids for enhancing multi-response characteristics", *Wear* 426–427 (2019) 877–886
6. Kasper Ringgaarda, Yaser Mohammadib, Christian Merrildc, Ole Ballinga, Keivan Ahmadib, (2019): "Optimization of material removal rate in milling of thin-walled structures using penalty cost function", International *Journal of Machine Tools and Manufacture* 145 (2019) 103430
7. I.A. Daniyana, I. Tlhabadirab, O.O. Daramolac, S.N. Phokobyed, M. Siviwed, K. Mpofua, (2020): "Measurement and optimization of cutting forces during M200 TS milling process using the response surface methodology and dynamometer, Procedia CIRP 88 (2020) 288–293
8. Lucas Guedes de Oliveira, Carlos Henrique de Oliveira, Tarcísio Gonçalves de Brito, Emerson Jos´e de Paiva, Anderson Paulo de Paiva, Joao Roberto Ferreira, (2020): "Nonlinear optimization strategy based on multivariate prediction capability ratios: Analytical schemes and model validation for duplex stainless steel end milling", *Precision Engineering* 66 (2020) 229–254
9. B Schmucker, F Trautwein, R Hartl, A Lechler, M F Zaeh, A Veerl, (2022): "Online Parameterization of a Milling Force Model using an Intelligent System Architecture and bayesian Optimization", Procedia CIRP 107 (2022) 1041–1046
10. Al Mazedur Rahmana, S M Abdur Roba, Anil K. Srivastavaa, (2021): "Modelling and optimization of process parameters in face milling of Ti6Al4V alloy using Taguchi and grey relational analysis", Procedia Manufacturing 53 (2021) 204–212
11. Lei Liu, Da Qu c, Huajun Cao, Xuefeng Huang, Yang Song, Xinzhen Kang, (2022): "Process optimization of high machining efficiency and low surface defects for HSD milling UD-CF/PEEK with limited thermal effect", *Journal of Manufacturing Processes* 76 (2022) 532–547
12. Pengfei Ding, Xianzhen Huang, Xuewei Zhang, Yuxiong Li, Changli Wang, (2022): "Reliability optimization of micro-milling cutting parameters using slime mould sequence algorithm", *Simulation Modelling Practice and Theory* 119 (2022) 102575
13. M Shivasheshadri, M Arunadevi, P CPS Prakash, (2012): "Simulation approach and optimization of machining parameters in CNC milling machine using genetic algorithm", *International Journal of Engineering Research & Technology* (IJERT) (Vol.1 Issue/ 10, ISSN: 2278-0181).
14. Varsharani Gaike, Jambeswar sahu, Raju pawade, (2018): "Optimization of cutting parameters for cutting ForceMinimization in Helicall Ball end milling of Inconel 718 by using genetic algorithm",Procedia CIRP 77 (2018) 477–480
15. S.L. Campanelli, G. Casalino, N. Contuzzi, (2013): "Multi-objective optimization of laser milling of 5754 aluminum alloy", *Optics & Laser Technology* 52(2013) 48–56