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Development of a Two Stage Prediction Model for Material Removal Rate During CNC Turning Operations – An Investigative Study.

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ABSTRACT: This paper is based on the development of a two-staged prediction model using output from experimental machinability studies on machining Chrome Steel in a CNC Machine, so as to predict the MRR (Material Removal Rate) using a two stage prediction process involving application of Artificial Neural Network (ANN) model and then using a Multiple Regression model to refine the results. The input parameters considered for the background study on machinability of chrome steel includes the Cutting speed, Feed rate, Depth of cut and the Coolant proportions. The effort in the prediction process for the MRR a priori assist the machinist in selection of the best combination the four critical input parameter values that can maximize the MRR. The development study in the current research has deployed a two staged predictions approach. The first stage uses a selection of nine best combinations of the four input parameters. This data set is then used as input into the ANN Model in three steps of training, testing and predicting the output as the response variable in this case being model for predicting the MRR. The initial data set obtained from the background study was used to train the model using the ANN algorithm. The trained data set obtained was then used to test and subsequently used to predict values of the MRR which indicates the rate of production during the CNC turning operation. The simulated experimental runs were carried out using the four factors at three levels each. Thus a total of 81 trials were run in the simulation platform in the two stage prediction approach. The ANN Model was run on a software platform used for risk assessment and evaluation namely Palisade and later the output of the ANN is used for building an empirical model using the Multiple Linear Regression(MLR)approach. The regression model was constructed using the Minitab Release 17 platform. The inputs for the MLR model were the parameter setting predicted using ANN. The output summary from the two platforms indicates that coefficient of determination values were 0.9973 (99.73% contribution due to the model). The R-Square (Adjusted) values from the model were to be 99.73% and the R-Square (Predicted) to be 99.71%. The approach used in this study using the two stage model for predicting machinability of chrome steel as a function of the critical input parameters, clearly demonstrate the level of accuracies that can be obtained using intelligent algorithms. The study has significance in evolving the recommendation for setting the parameters during the CNC turning operations on any materials used during research investigations. This study can be further extended by incorporating a multistage refinement using various other intelligent algorithms in combination, to further improve the accuracies of predictions.

KEYWORDS: MRR, ANN, Machinability, Algorithms, Regression, CNC turning, R-Square.

1. INTRODUCTION

Machinability studies are important in the process of developing an understanding of the machining parameters that influence the quality of surface finish and the material removal rate. Surface finish represents the Quality of the surfaces obtained through the machining processes and material removal rate indicate the rate of outputs that can be obtained. The Current investigation has been carried out on

Chrome Steel as the basic raw material. Chrome steel is widely preferred material for the manufacture of Bearings.

The researchers in this field have mentioned about the tremendous scope for work in this area. Studies to continuously improvise on the methods of upgrading the quality of the surface finish of the bearings and such other functionally important machined components are important from the application viewpoints. [1]. Surface Finish of the product as the quality characteristic is gaining importance in today's Industrial era as it directly reflects the functional ability of the machined components. A few applications of ANN-based input-output relationship modeling for metal cutting operations are also found mention in the open literature. The literature is with regard to choosing the better machining parameters for obtaining better surface roughness during different machining parameters. Chienand Chou [2] in his work has presented an ANN model to predict the surface roughness of AISI304 stainless steel and estimates the cutting forces and the tool life. In the same work genetic algorithm was used to determine the optimum cutting parameters for the material removal rate under the constraints of the surface roughness. Nabil and Ridha [3] in their publication introduced an approach that combined the design of experiments (DOE) and the ANN to set up accurate models for ground surface roughness parameter predictions**.** The current research study uses the approach to analyze and investigate a two stage prediction models for predicting surface roughness of CNC turning operation. The two staged prediction involves the application of ANN models and the multiple regression models. It has been determined that improvements in the values of the co-efficient of determination and precision of predication can be enhanced using this approach.

2. BACKGROUND STUDIES ON MACHINABILITY ANALYSIS: -

The Experimental set up during the investigation were as follows: Tungsten carbide tool was used for machining operations. The specimens were prepared based on the ASTM standards and recommendation; the Surface roughness was measured using Surf Test. The dimensions of the specimen work piece were as follows: Length- 150mm, Diameter 40mm, Weight of the part 1.5kg and the entire experimental study was conducted on the CNC machine named 'JobberXL'. This CNC machine is provided by machine tool builder namely Ace Micromatic.

2.1 Selection of work piece material for the experimentation:

The work piece material selected was chrome steel namely 100Cr$_6$. The reason for selection of this material is that it is widely used in the manufacture of bearing components. Bearings demand high grades of Surface Finish as a property, post the machining operations.

The chemical compositions, density and hardness of chrome steel 100Cr$_6$ used in the investigation is as tabulated in Table.2.1.1 and Table.2.1.2 respectively.

TABLE 2.1.1 CHEMICAL COMPOSITION OF 100Cr6

	Carbon (%)	Manganese (%)	Silicon (%)	Phosphorous (%)	Sulphur (%)
100Cr6	0.97	0.41	0.19	0.01	0.01
	Chromium (%)	Molybdenum (%)	Lithium (%)	Aluminium (%)	Copper (%)
100Cr6	1.43	0.05	0.10	0.01	0.11

TABLE 2.1.2 DENSITY AND HARDNESS OF 100Cr6

	100Cr6
Density	7.83 g/cm^3
Hardness	64HRC

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2.2. Input parameters chosen for the experimentation:

The input parameter chosen for machining operation on chrome steel are cutting speed, feed rate, and depth of cut along with coolant proposition with three levels of variation such as low, medium and high. And respective values chosen are as tabulated in below table – 2.2.1.

TABLE2.2.1 INPUT PARAMETERS CHOSEN FOR MACHINING OPERATION

	Low	**Medium**	**High**
	1	**2**	**3**
Cutting Speed(rpm)	800	1200	1600
Feed Rate(mm/rev)	0.05	0.1	0.15
Depth of Cut(mm)	0.5	0.75	1.00
Coolant Proportion	1:30	1:20	1:10

2.3 Experimental parameters used to train Artificial Neural Network (ANN) algorithm:

Experimental parameters (cutting speed, feed rate, depth of cut, and coolant proportion) along with the respective response MRR (material removal rate) obtained by physical experimentation is as tabulated in table 2.3.1 and the same being used as training data in the system of artificial neural network (ANN) algorithm to make prediction for MRR values for other set of input parameter values.

TABLE2.3.1: NINE COMBINATIONS OF EXPERIMENTAL PARAMETERS ALONG WITH RESPECTIVE RESPONSE FROM PHYSICAL EXPERIMENTATION

Cutting Speed (rpm)	Feed rate (mm/rev)	Depth of Cut (mm)	Coolant Proportion	MRR (mm3/s)
800	0.05	0.5	1:30	2800.99
800	0.1	0.75	1:20	7643.68
800	0.15	1	1:10	14304.53
1200	0.05	0.75	1:10	5637.65
1200	0.1	1	1:30	14128.35
1200	0.15	0.5	1:20	12816.09
1600	0.05	1	1:20	9633.52
1600	0.1	0.5	1:10	11270.09
1600	0.15	0.75	1:30	22362.15

3. METHODOLOGY FOR THE TWO-STAGE PREDICTION MODEL: -

Intelligent algorithm can be effectively applied in manufacturing environment with an objective to predict the output level/desired results of machining process without having investment on resources and time, which are very much essential for physical experimentation. These predicted output values of machining process in a cost-effective way will help in improvising the output levels of machining and thereby to achieve the desired results. This investigation is structured to have two stage predictions. Each stage efficiently estimates the response i.e. Material Removal Rate (MRR) for any given combination of experimental parameters, without conduction of physical experimentation, resulting in saving material cost, machining cost and prominently time investment.

The two-stage prediction model comprises of Artificial Neural Network model (ANN) as stage -1 prediction, outcome of which is input into stage -2 prediction namely Multiple Linear Regression (MLR).

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This investigation was structured to have two stages of prediction to improvise the precision of estimating the required response value i.e. Material Removal Rate (MRR).

Figure 3.1 reflects the proposed two stage prediction model for predicting material removal rate (MRR) regarding chrome steel material. Two stages of implemented prediction models are described in succeeding paragraphs of this section.

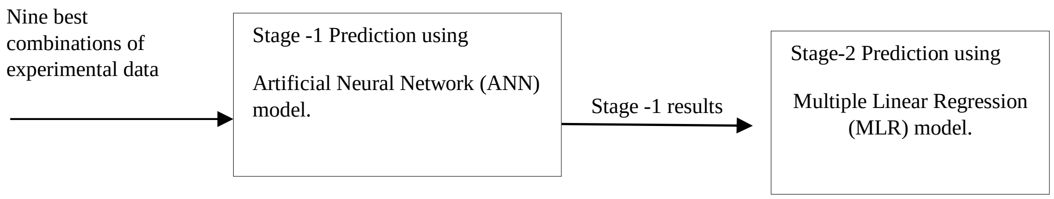

FIG -3.1: PROPOSED TWO STAGE PREDICTION MODELS FOR PREDICTION OF MACHINABILITY OF CHROME STEEL MATERIAL

3.1 Description of two stages of prediction model:

This section describes the two stages of prediction model used in this investigation with an objective to improvise the machinability of chrome steel on CNC machine by precisely predicting values for Material Removal Rate (MRR) for any combination of input parameters using artificial intelligence.

3.1.1 Artificial Neural Network (ANN) – Stage 1 Prediction:

An artificial neural network (ANN) can be defined as a computational model based on the structure and functionality of biological neural networks. There are several advantages of artificial neural network but one of the most recognized of these is the fact that it can actually learn from observing data sets that is inputted into it during the training stage of neural network. An ANN model can be regarded as the most cost-effective and ideal method that can be adopted for arriving at solutions while defining computing functions or distributions. And also that artificial neural network takes data samples rather than entire data sets to arrive at solutions, which can improvise both cost and time effectiveness. The steps employed in ANN algorithm are discussed in below section.

Step 1- Training the neural network: Nine combination of data involving four input parameters and respective resulted Material Removal Rate(MRR) which was obtained by physical conduction of experimentation are used to train the neural network.

Step 2 – Testing the neural network:81 treatments with all possible combination of four input parameter according to orthogonal array was used to test the already trained neural network on nine best combination of data set in the previous step. This step reflects the number of good and bad prediction cases existed in the entire 81 treatments.

Step-3 – Prediction of MRR value for 81 treatments by using the tested neural network: This is the final stage of ANN model, under which trained and tested neural network is used in fetching MRR values for 81 different combinations of four input parameters without conduction of physical experimentation.

3.1.2 Steps in Multiple Linear Regression (MLR) - Stage 2 Prediction:

Multiple Linear Regression (MLR) is the most common form of linear regression analysis. As a predictive analysis, the multiple liner regression is used to explain the relationship between one continuous dependent variable and two or more independent variables. Following are the steps executed in multiple linear regression (MLR) for making stage 2 prediction using the results obtained after stage 1 prediction i.e. prediction of MRR using ANN algorithm.

Step-1: Output of the ANN model was input into the Multiple Linear Regression (MLR) model which was developed using the Minitab Release 17 platform.

Step-2: Regression analysis of MRR (Dependent variable) versus cutting speed, feed rate, depth of

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cut and coolant proportion (Independent variables) was executed.

Step-3: Residual plots for MRR (mm3/s) were generated to study the precision of prediction by the model.

4. RESULT AND DISCUSSIONS

This current study is an attempt in predicting material removal rate (MRR) for a machining process on CNC turning machine for the material chrome steel using a set of nine combinations of four input parameters (Cutting speed, Feed rate, Depth of cut and Coolant proportion) which are influencing the material removal rate (MRR). Two staged prediction methodology was implemented for achieving this above stated purpose. Artificial Neural Networks (ANN) was used as stage-1 prediction and subsequently Multiple Linear Regression (MLR) as stage-2 prediction. Results from each stage of prediction is discussed in succeeding paragraphs of this section.

4.1 Results of stage 1 – prediction using Artificial Neural Network

Neural Networks in Palisade software is trained on set of nine combinations of four input parameters used in machining the Chrome steel material and the response factor being the Material Removal Rate (MRR) achieved during the machining operation. Further the trained neural network was tested to produce MRR values for 81 possible combinations of four input parameters, followed by prediction stage, which improved the number of good predictions by reducing the bad predictions from previous stage of ANN model i.e. testing stage.

Predicted values of MRR obtained using ANN model of palisade software are tabulated in table -4.1.1, summary obtained from palisade software is shown in table -4.1.2, graph -4.1.1 depicting the histogram of residuals after execution of prediction step under ANN model and graph – 4.1.2 showing a plot of actual verses predicted values after execution of prediction step under ANN model.

TABLE -4.1.1: TABULATION OF PREDICTIONS FOR MRR OBTAINED USING ANN MODEL OF PALISADE SOFTWARE

Sl No	Cutting Speed (rpm)	Feed rate (mm/rev)	Depth of Cut (mm)	Coolant Proportion	MRR(mm3/s)	Sl No	Cutting Speed (rpm)	Feed rate (mm/rev)	Depth of Cut (mm)	Coolant Proportion	MRR(mm3/s)
1	800	0.05	0.5	1/30	2800.99	42	1200	0.1	0.75	1/10	9568.81
2	800	0.05	0.5	1/20	1321.846	43	1200	0.1	1	1/30	14128.35
3	800	0.05	0.5	1/10	1109.48	44	1200	0.1	1	1/20	13317.91
4	800	0.05	0.75	1/30	3450.061	45	1200	0.1	1	1/10	10886.58
5	800	0.05	0.75	1/20	2639.619	46	1200	0.15	0.5	1/30	17643.21
6	800	0.05	0.75	1/10	208.2947	47	1200	0.15	0.5	1/20	16832.77
7	800	0.05	1	1/30	4767.834	48	1200	0.15	0.5	1/10	14401.45
8	800	0.05	1	1/20	3957.393	49	1200	0.15	0.75	1/30	18960.98
9	800	0.05	1	1/10	1526.068	50	1200	0.15	0.75	1/20	18150.54
10	800	0.1	0.5	1/30	8282.696	51	1200	0.15	0.75	1/10	15719.22
11	800	0.1	0.5	1/20	7472.254	52	1200	0.15	1	1/30	20278.76
12	800	0.1	0.5	1/10	5040.93	53	1200	0.15	1	1/20	19468.32
13	800	0.1	0.75	1/30	9600.469	54	1200	0.15	1	1/10	17036.99
14	800	0.1	0.75	1/20	7643.68	55	1600	0.05	0.5	1/30	8552.502
15	800	0.1	0.75	1/10	6358.703	56	1600	0.05	0.5	1/20	7742.06
16	800	0.1	1	1/30	10918.24	57	1600	0.05	0.5	1/10	5310.736

17	800	0.1	1	1/20	10107.8	58	1600	0.05	0.75	1/30	9870.275
18	800	0.1	1	1/10	7676.477	59	1600	0.05	0.75	1/20	9059.834
19	800	0.15	0.5	1/30	14433.1	60	1600	0.05	0.75	1/10	6628.509
20	800	0.15	0.5	1/20	13622.66	61	1600	0.05	1	1/30	11188.05
21	800	0.15	0.5	1/10	11191.34	62	1600	0.05	1	1/20	9633.52
22	800	0.15	0.75	1/30	15750.88	63	1600	0.05	1	1/10	7946.283
23	800	0.15	0.75	1/20	14940.44	64	1600	0.1	0.5	1/30	14702.91
24	800	0.15	0.75	1/10	12509.11	65	1600	0.1	0.5	1/20	13892.47
25	800	0.15	1	1/30	17068.65	66	1600	0.1	0.5	1/10	11270.09
26	800	0.15	1	1/20	16258.21	67	1600	0.1	0.75	1/30	16020.68
27	800	0.15	1	1/10	14304.53	68	1600	0.1	0.75	1/20	15210.24
28	1200	0.05	0.5	1/30	5342.394	69	1600	0.1	0.75	1/10	12778.92
29	1200	0.05	0.5	1/20	4531.953	70	1600	0.1	1	1/30	17338.46
30	1200	0.05	0.5	1/10	2100.628	71	1600	0.1	1	1/20	16528.02
31	1200	0.05	0.75	1/30	6660.168	72	1600	0.1	1	1/10	14096.69
32	1200	0.05	0.75	1/20	5849.726	73	1600	0.15	0.5	1/30	20853.32
33	1200	0.05	0.75	1/10	5637.65	74	1600	0.15	0.5	1/20	20042.88
34	1200	0.05	1	1/30	7977.942	75	1600	0.15	0.5	1/10	17611.55
35	1200	0.05	1	1/20	7167.5	76	1600	0.15	0.75	1/30	22362.15
36	1200	0.05	1	1/10	4736.175	77	1600	0.15	0.75	1/20	21360.65
37	1200	0.1	0.5	1/30	11492.8	78	1600	0.15	0.75	1/10	18929.33
38	1200	0.1	0.5	1/20	10682.36	79	1600	0.15	1	1/30	23488.87
39	1200	0.1	0.5	1/10	8251.037	80	1600	0.15	1	1/20	22678.42
40	1200	0.1	0.75	1/30	12810.58	81	1600	0.15	1	1/10	20247.1
41	1200	0.1	0.75	1/20	12000.13						

TABLE.4.1.2 SUMMARY OBTAINED USING PALISADE SOFTWARE FOR THE PREDICTION STAGE OF ANN MODEL

Summary	
Net Information	
Independent Category Variables	1 (Coolant Proportion)
Independent Numeric Variables	3 (Cutting Speed (rpm), Feed rate (mm/rev), Depth of Cut (mm))
Dependent Variable	Numeric Var. (MRR(mm3/s))
Prediction	
Number of Cases	81
% Bad Predictions (with 30% Tolerance)	0.0000%
Root Mean Square Error	636.78
Mean Absolute Error	503.57
Std. Deviation of Abs. Error	389.75

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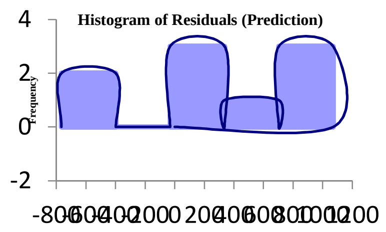
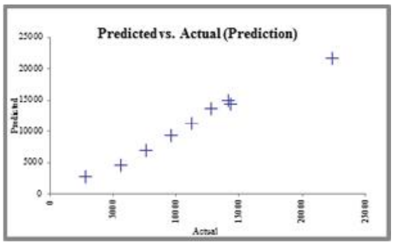


GRAPH 4.1.1: Histogram of residuals after prediction stage of ANN model



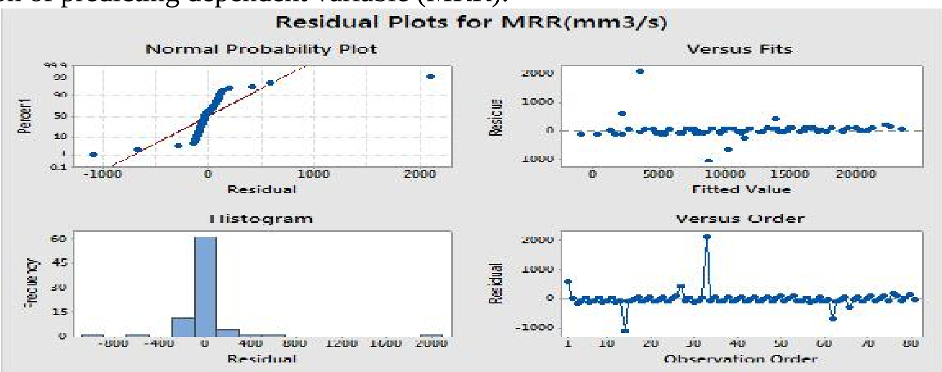
GRAPH 4.1.2: Prediction versus Actual values of MRR (mm3/s)

In regression analysis, the difference between the observed value of the dependent variable and the predicted value is called the residual. Graph.4.1.1 is depicting histogram of existed residual between the actual values of MRR obtained from background studies by conduction of experimentation and the predicted values from ANN model, and Graph 4.1.2 is depicting the plot of predicted values of MRR after effecting three stages of ANN model namely train, test and prediction against actual experimentation values from background studies, its seen from the graph that there is much deviation between the two exists hence co-efficient of determination is good, further predicting precision can be improved by adopting another efficient model for prediction.

4.2 Results of stage 2- Prediction using Multiple Linear Regression (MLR) model:

Multiple Linear Regression(MLR) is the most common form of linear regression analysis. As a predictive analysis, the multiple linear regression is used to explain the relationship between one continuous dependent variable (MRR) and two or more independent variables (Cutting speed, feed rate, depth of cut, coolant proposition).

MLR model is developed using the Minitab Release 17 platform as stage-2 predictions in improvising the precision of predicting dependent variable (MRR).



SCREEN SHOT -RESIDUAL PLOTS FOR MRR (MM^3/S) FROM MLR MODEL

Screen shot obtained from Minitab Release 17 platform, depicting residual plots for prediction of MRR values (Material Removal Rate) for 81 treatments is as shown above.

Normal Probability plot reflects no severe departure from normality, since the residuals fall approximately along the straight line, Versus Fits indicates that the assumption of constant variance is satisfied by the data integrated to MLR model, Histogram reflects zero residual existence for all most sixty observations and there by justifying the precision with which ANN model predicted the MRR values.

5. CONCLUSIONS:

The research directed at developing an effective prediction model using a proposed two stage intelligent modeling approach based on artificial neural network and empirical modeling using multiple regression for predicting material removal rate during turning operation on CNC Machines.

In the study, chrome steel material with grade 100Cr6 was selected. The two stage prediction comprised of applying ANN (Artificial Neural Network) on the machinability data set as stage -1 prediction and then using MLR (Multiple Linear Regression) as stage -2 predictions, the first stage prediction has used nine best combinations of the four input parameters and the results of MRR values which were obtained from experimentation during the conduction of background studies. ANN model contained three steps namely training; testing and prediction, upon successful completion of all the three MRR values were predicted for 81 treatments with 0.997 coefficients of determination. Further to improvise the precision of determining MRR (Material Removal Rate), results from ANN model were used as inputs into the Multiple Linear Regression model development using Minitab Release 17 platform. The research has proved that the obtained two stage prediction are effective in refining the accuracy of the MRR values. The indicators of the goodness of the prediction namely the R-square, R-Square (Adjusted), and R-Square (Predicted) values were found to be 99.75%, 99.73% and 99.71% respectively. This approach of two-stage prediction model is found to be an effective technique to predict Material Removal Rate (MRR) for any combination of influencing input parameters, well before the actual machining operation on CNC machine, hence this technique can drive the cost and time saving efforts in the machining operations. These techniques prominently help in deciding on best combination of input parameters that can be employed to achieve excellent Material Removal Rate (MRR) and thus required surface roughness for machining operations on CNC machine. (Chrome steel material 100Cr6 is used in this investigation report). The research can be further extended to build and develop multistage prediction models.

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