International Journal of Scientific Research in Engineering and Management (IJSREM)
Volume: 07 Issue: 09 | September - 2023 SJIF Rating: 8.176 ISSN: 2582-3930

Analysis of Machining Parameters for Turning of AL-6061 and Optimization

Dr. Qasim Murtaza[1], Baibhav Kumar[1], Anant Vohra[2] Anshuman Piyush[3]

[1]*Professor , Department of Mechanical Engineering, Delhi Technological University, New Delhi, India*
[1]*Undergraduate Student, Department of Mechanical Engineering, Delhi Technological University, New Delhi, India*
[2]*Undergraduate Student, Department of Mechanical Engineering, Delhi Technological University, New Delhi, India*
[3]*Undergraduate Student, Department of Mechanical Engineering, Delhi Technological University, New Delhi, India*

***Abstract*: The paper shows and includes targeted supervision of optimizing machining parameters. Material Removal Rate and surface roughness being integral to machining efficacy of any workpiece , simulation based modeling helps in failure mitigation.Thepotential of ANN-GA mathematical approach for prediction and optimization of MRR and surface roughness of AL 6061 , a analysis based statistical study has been discussed. The computational model between the desired output and the inputs have been configured using Multiple Regression- Genetic Algorithm and Artificial Neural Network(ANN) methods. The closeness in predicted and optimized data sets were mapped using integrational ANN with GA to interpolate efficacy in optimality.**

Keywords: Artificial Neural Network(ANN)k, Material Removal Rate(MRR), Genetic algorithm(GA), Surface roughness , depth of cut , feedrate , Regression analysis, ANOVA
.

1. Introduction

The industrial machining requirements calls for the need of precision and manufactured product efficacy. The diverse machining processes and its role in shaping final product has crucial role making products industrially ready. Turning operation on horizontal lathe machine is one of those integral machining operation , where by cylindrical surfaces of required diameter consideration and surface profile is achieved. Turning being work piece driven and single point cutting tool driven machining, economics of industrial manufacturing necessities for optimal machining parameter selection to simulate desired output without any catastrophic manufacturing. ANN being an widely looked up tool where by multiple machining parameter can be architected into input, hidden and output layers , ability to use learning outcomes in training sets. Aluminum 6061 alloyis one of integral industrial friendly alloy which makes its presence in several applications like aviation components, automobile parts, weapon casings, and high vacuum chambers. These industries look for low allowance operational values andutmost precision is desirable in these respective manufacturing. The inclusion of Artificial Neural Networks mitigates with missing data and machining parameters learn by examples, making real-time simulated modelling possible. With exclusively integrating with GA , optimization of Discrete MRR outputs in turning operation can be predicted even with due considerations of minute errors in the inputs, with quick inheritance and good accuracy.

2. Literature Review

Ramu I. et.al [7] explained and demonstrated a systematic procedure of Taguchi parameter design and applying it to the data onturning. The second was to find out the optimal combination of process parameters based on S/N ratio and to know the significance of each parameter by performing ANOVA analysis.

T.M. Chenthil Jegana et.al [1] This paper covers an important aspect and brings how ANN should be equipped with suchfunctionalities as storing information, reasoning, decision making, learning, and integration of these into the process. In particular, the learning characteristic is a unique feature of the ANN Turning operation optimization.

Tiagrajah V jannharimal et.al [8] discusses effective, Multi Objective Genetic Algorithm (MOGA) will act as an optimizer of thedeveloped model. Turning input parameters such as feed rate, cutting speed and depth of cut were considered as input variables and surface roughness, specific power consumption and cutting force were used as output variables.

S. Nes¸eli et.al [2] highlights tool geometry on the surface finish obtained in turning of AISI 1040 steel. In order to find out the effect of tool geometry parameters on the surface roughness during turning, response surface methodology (RSM) was used and a prediction model was developed related to average surface roughness (Ra) using experimental data. The results explained

that the tool nose radius was the dominant factor on the surface roughness.

Ndaruhadi, P.Y.M.W et.al [4] helps in assessing surface roughness value t was found that feed did not significantly influence surface roughness. Among the influencing factor, the rank is tool type, cutting speed, and cutting direction.

Dhabale, R et.al [6] presents a new idea to generate process plan from feature-based modeling, based on an inclusive of geometric modeling method that proposes both feature-based modeling and feature information storage.

3. Experimental studies and datasets

Table 1. Dataset

Run Order	*Speed (RPM)*	*Feed Rate (mm/min)*	*Depth of Cut (mm)*	*MRR (mm^3/min)*	*Ra (µs)*
1	180	0.2	0.2	113.927	1.04
2	180	0.2	0.4	212.018	0.98
3	180	0.2	0.6	261.698	2.2
4	180	0.315	0.2	672.129	2.44
5	180	0.315	0.4	333.569	3.84
6	180	0.315	0.6	897.738	2.4
7	180	0.4	0.2	22.443	2.06
8	180	0.4	0.4	953.491	2.3
9	450	0.4	0.6	901.732	3.66
10	450	0.2	0.2	780.859	0.9
11	450	0.2	0.4	528.915	0.94
12	450	0.2	0.6	145.761	2.9
13	450	0.315	0.2	176.76	1.42
14	450	0.315	0.4	303.637	3.38
15	450	0.315	0.6	2263.05	1.34
16	450	0.4	0.2	40.271	1.74
17	450	0.4	0.4	890.513	1.94
18	710	0.4	0.6	4822.2	2.88
19	710	0.2	0.2	130.586	0.86
20	710	0.2	0.4	744.814	0.92
21	710	0.2	0.6	2862.91	1.98
22	710	0.315	0.2	592.809	1.14
23	710	0.315	0.4	3098.48	1.22
24	710	0.315	0.6	9365.24	1.16
25	710	0.4	0.2	948.858	1.2
26	710	0.4	0.4	5658.57	1.38

The above table of datasets depicts input parameters considered for turning operation Like the feed rate , depth of cut, cutting speeds and corresponding Material Removal Rate obtained . The machining parameters considered was kept in accordance with industrial requirements of turning operations on AL 6061 . AL 6061 being industrially proclaimed as a medium to high strength heat-treatable alloy with desirable strength .It also has very good corrosion resistance and very good weldability. The chemical composition consideration 6061 aluminium is 97.9% Al, 0.6% Si, 1.0%Mg, 0.2%Cr, and 0.28% Cu. The density of 6061 aluminium alloy is 2.7 g/cm3 with great formability and workpiece can be machined using turning operation to meet industrial demands.

The objective of carrying our research on given dataset is to model conventional turning operation to infer optimal value of material removal rate and surface roughness to enhance precision and accuracy of machining.

4. Methodology

The experimental results were assessed on design and modeling level by taking considerations of Taguchi Method and MRR –surface roughness were assessed based on response of predicted data statistically without remotely performing set experiments. The experimental results derived in original experimental research are in synchronization to the ANN predicted results.

The MATLAB nn toolbox is integrated for training and testing of neural network model. The results inferred using Artificial Neural Network (ANN) indicate good agreement between the predicted output values and that of experimental values. Thereafter , Genetic Algorithm (GA) is made inclusive with neural network model to determine the optimal machining parameters feed rate, depth of cut and cutting speed to get desired industrial demand in accordance to needs of optimal Material removal rate and surface roughness inturning operation.

The due considerations of exploration in data analysis were looked into for establishing relationship between input and output variables, The mentioned integration assessed the non-linearity between parameters. Due to unavailability of solutions for non-linearity, ANN was integrated into our project for its ability to learn and model complex solutions.

5. Development Artificial Neural Networks

Artificial Neural networks are the framework that are intended to reproduce the working of a human mind. With the assistance of involvement and information Artificial Neural Network works on itself utilizing artificial neurons. Artificial Neural Network comprise of rudimentary units called as neurons which takes at least one sources of info and produces a result.

Computations that are carried out on each neuron if ANN are as follows:

$$z[i] = w[i] * A[i-1] + b[i]$$

$$A[i] = f(Z[i])$$

Here the notations are as follows:

$W^{[i]}$ represents the weight of the neuron

$A^{[i-1]}$ represents the output derived form last layer

$b^{[i]}$ represents the bias of the connection

f(x) represents the non linear activation function

A neural network consists of several layers which are grouped as input layer, hidden layer and output layer. Here layer means theset of parallel neurons without having connections between them. Neurons from input layer are connected to hidden layer which in turn is connected to the output layer in the whole Artificial Neural Networks System

In our model we have used Gradient Descent back propagation method for the best tuning of the neurons present in each layer

For our model we have used MATLAB nntool for training and obtaining of Artificial Neural Network. and results associated with the Neural networks.

For ANN in MATLAB we first imported classified our dataset into input set which include input parameters viz. Cutting Speed, Depth of Cut, Feed Rate and after classification of Input data we had made another classification which was target set that includedata of output parameters viz. Material Removal Rate and Surface Roughness.

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A neural network comprises of various configurations such as type of network used, Training function, Learning function, Transfer function, number of neurons in input, hidden and output layers and number of epochs. To get the best result it is veryimportant to have best value for these configurations. The table below has listed down the functions and specifications that weused for our neural network.

Levenberg- Marquardt algorithm is taken as the training function due to its wide applications in solving non-linear problems by curve fitting and Mean Square error function is chosen as the performance function for accurate model.

To get the accurate neural network model by tuning weights and bias efficiently we have used Gradient descent back propagation technique.

Network Type	Feed Forward BackPropagation TRAINLM
Training function Adaptive Learning Function Performance Function	LEARNGDM
	MSE
Number of Layers	5Number of
Neurons in hidden layers Transfer FunctionNumber of	[5, 3, 4]
Epochs	TANSIG1000

Table 2. Neural Network Parameters

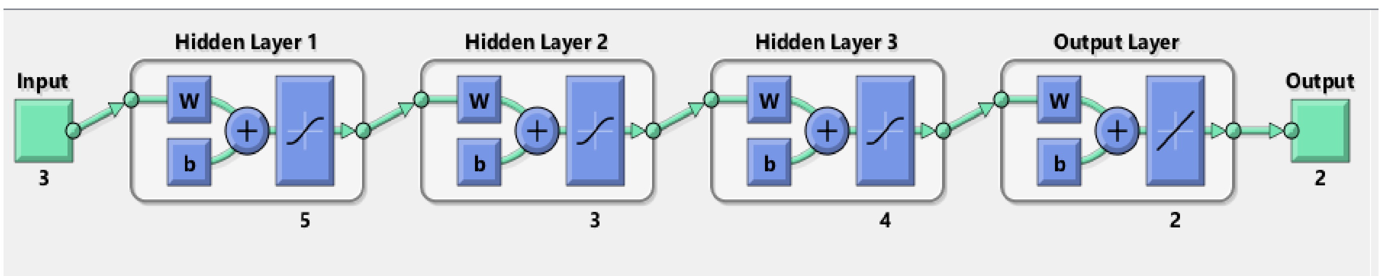

Fig.1 Neural Network Model in Matlab

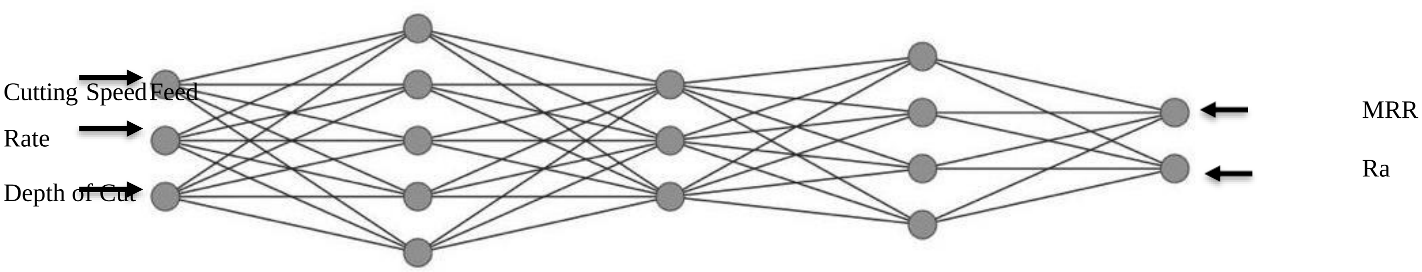

Fig.2 Neural Network Model Architecture

Stochastic Gradient Descent is the optimization algorithm used for adaptive learning as it minimizes the gradient and adjusts weights accordingly. Weights and biases are tuned in an iterative manner to obtain optimum values for least error.

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6. Results of Artificial Neural Networks

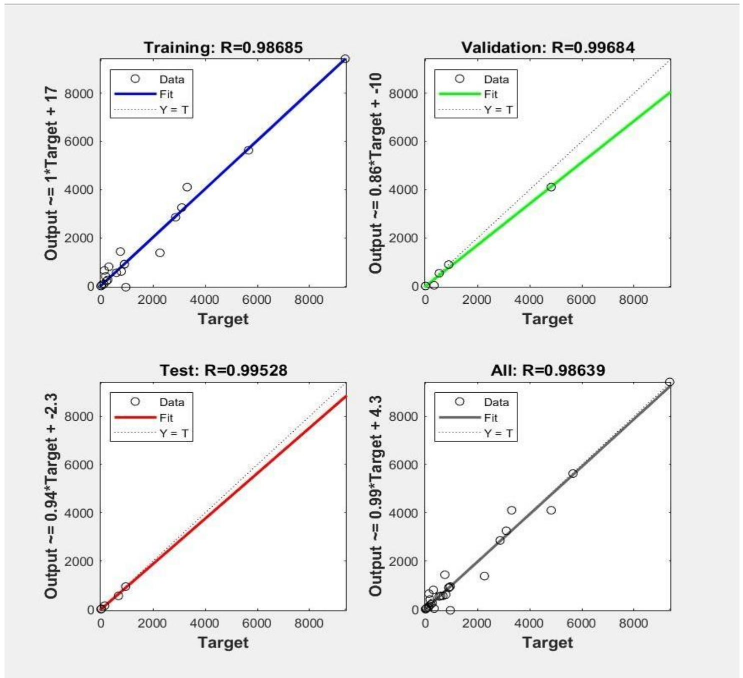
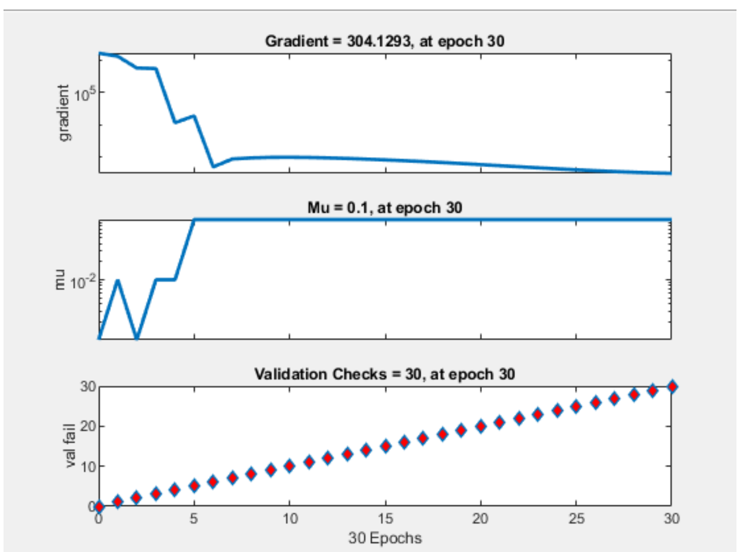


Fig.3 Régression Plots



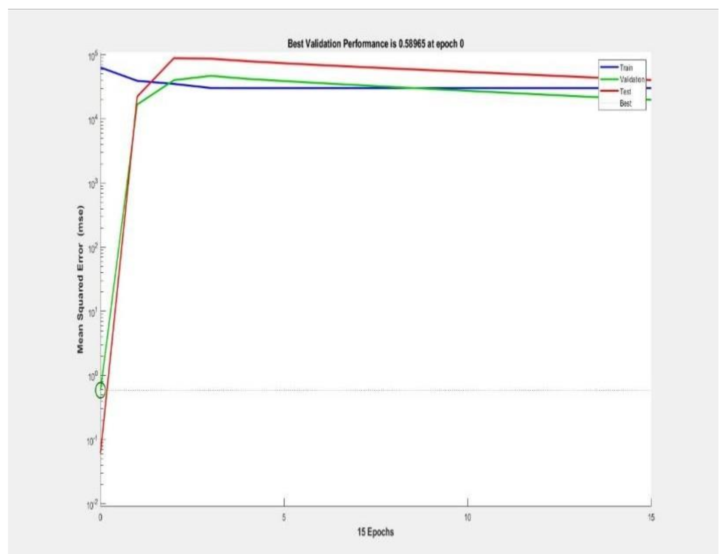


Fig.4 Validation Performance

Fig.5 Gradient Descent Plots

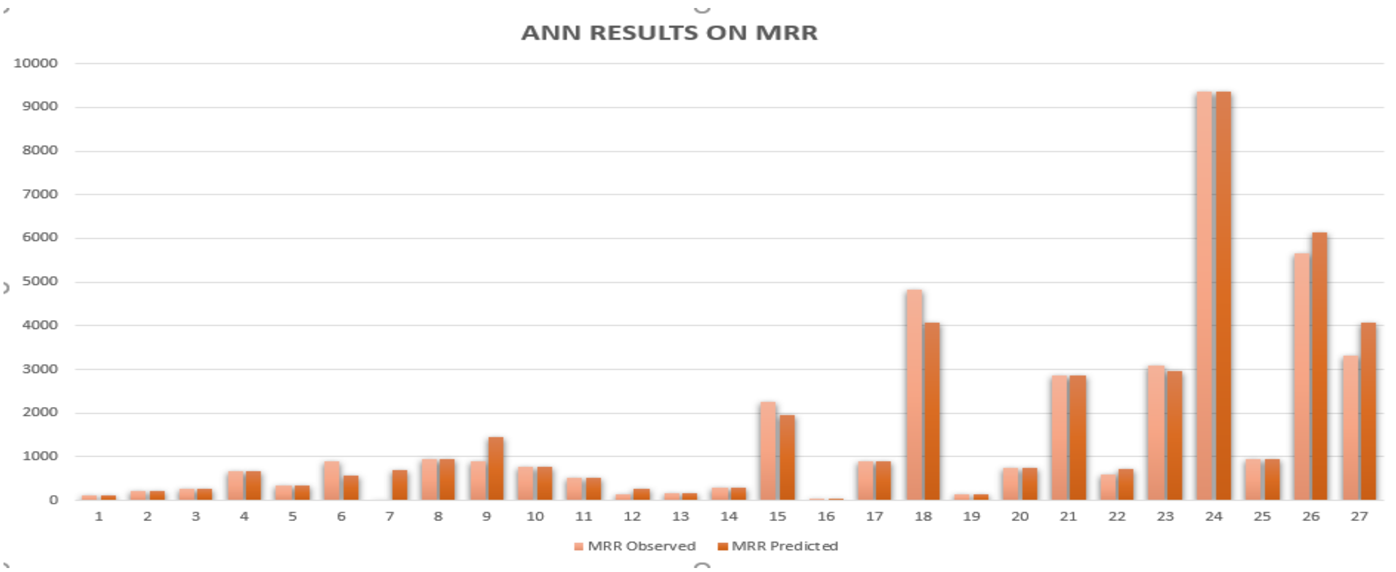


Fig.6 Observed Vs Predicted MRR

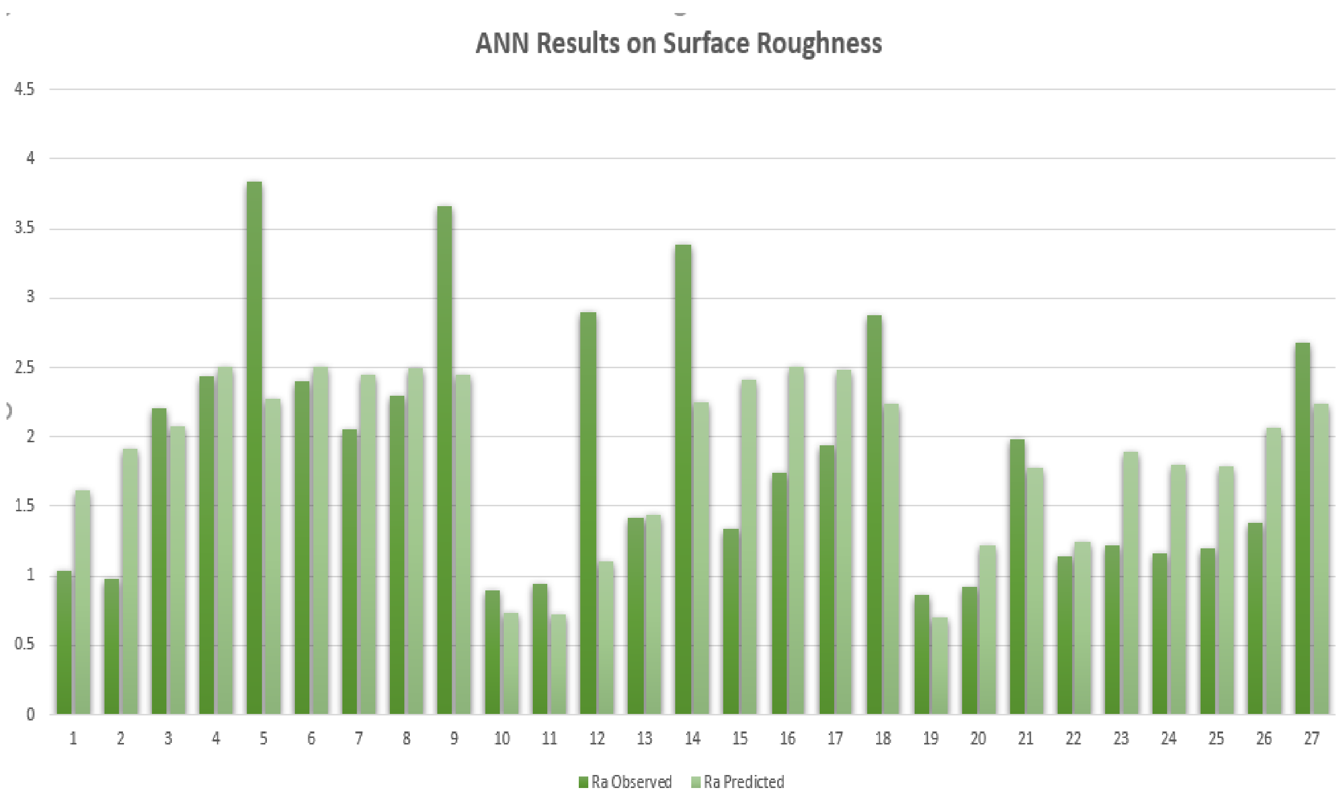


Fig.7 Observed Vs

S.No.	*Experimental* MRR (mm^3/min)	Ra (µs)	*Predicted* MRR (mm^3/min)	Ra (µs)
1	113.927	1.04	114.165	1.61
2	212.018	0.98	212.155	1.91
3	261.698	2.20	261.80	2.08
4	672.129	2.44	672.159	2.51
5	333.569	3.84	333.641	2.27
6	897.738	2.40	572.567	2.50
7	22.443	2.06	691.35	2.44
8	953.491	2.30	953.427	2.49
9	901.732	3.66	1461.130	2.44
10	780.859	0.9	781.045	0.73
11	528.915	0.94	529.102	0.72
12	145.761	2.9	260.810	1.11
13	176.76	1.42	177.068	1.44
14	303.637	3.38	303.654	2.24
15	2263.05	1.34	1942.553	2.41
16	40.271	1.74	40.401	2.50
17	890.513	1.94	890.598	2.48
18	4822.2	2.88	4064.131	2.24
19	130.586	0.86	130.751	0.70
20	744.814	0.92	744.989	1.21
21	2862.91	1.98	2863.012	1.78
22	592.809	1.14	720.44	1.24
23	3098.48	1.22	2958.771	1.89
24	9365.24	1.16	9365.190	1.79
25	948.858	1.20	948.953	1.78
26	5658.57	1.38	6147.365	2.07
27	3305.82	2.68	4064.131	2.24

Table 3. ANN Results

Table 3 above shows the experimental values and predicted values of Material Removal Rate (MRR) and Surface Roughness (Ra) achieved from Artificial Neural Networks. Regression results are also plotted in Fig.4 for training, testing and validation set where our model achieved the accuracy of 98.68% for training and 99.52% for testing set. The plots represents the fitting of model where R represents the square of observed and predicted relations. More the value close to 1 better are the results.
Apart from that Gradient descent visualization in Fig.5 and Validation performance in Fig.6 are also plotted. A comparison between the observed and predicted values of Material Removal Rate and Surface Roughness are also plotted in Fig. 7 and Fig.8 which shows how much predicted values are deviated from observed response.

7. Optimization using Genetic Algorithm

Genetic algorithm considerations include evolutionary revolution optimization which centers around natural selection, inheritance , mutations and crossovers.
The genetic algorithm considered to be trial and tested classical evolutionary algorithm. With inception of random means that in order to find a solution using the GA, random changes are integrated. Note that GA may be called Simple GA due to its ease input compared to other EAs.
GA is underlined on Darwin's theory of evolution. It is a slow gradual process that works by making changes to the making slightand slow changes. Also, GA makes slight changes to its solutions slowly until getting the best solution.

In a genetic algorithm, efficacy ensured population of candidate solutions (called individuals, creatures, or phenotypes) to an optimization problem is evolved toward better solutions. The choice of opting Genetic Algorithm in optimising turning operations points out to its easy compatibility and integrability compared to other parallel optimisation algorithms like Ant Colony optimisation, swarm optimisation and others.
The GA is known to immute the natural selection as proposed by Darwin and decodes algorithm best suited to give best possible predictions, optimality is configured for both MRR and surface roughness. The major flow practice includes following :

1. Selection (Reproduction)-
It is initialised first operator is based on selection criteria. It chooses the chromosomes from the population of parents , cross over and produce offspring. It is evident from evolution theory of "Survival of the fittest" given by Darwin.
There are many techniques involved for reproduction or selection operator such as-

I. Tournament selection
II. Ranked position selection
III. Steady state selection

2. Cross Over-
Population is enriched with better individuals after reproduction phase. Then crossover operator is integrated to the mating pool andcreate better strings. Crossover operator improves clones of good strings but does not create new ones. By recombining good individuals, the process is likely to create even better individuals.

3. **Mutation-**
Mutation is a background operator. Mutation of a bit includes flipping it by changing 0 to 1 and vice-versa. After crossover, the mutation operator subjects to the strings to mutation. It facilitates a sudden change in a gene within a chromosome.
Thus, it allows the algorithm to see for the solution far away from the current ones. It ensures that the search algorithm is not trappedon a local optimum. The main consideration of this background operator is to prevent early convergence and maintain diversity within the population. The added advantage of performing modal state with behavioural integration is appreciable.

7.1 Response Surface Methodology

Response surface methodology is an integral mathematical tool which associates with modelling and assessment of problems in which a response of interest is influenced by several variables, and the objective is to reach out to optimal value. The inclusion ofRSM,

Relationship between the preferred response and independent input variables could be produced as:

$$Y = f(x_1, x_2, x_3, \ldots\ldots\ldots\ldots x_n) \pm e_r$$

Where,

y -preferred response, f -

response function (or

response surface),

$x_1, x_2, x_3, \ldots, x_n$ - independent input variables,

er - fitting error

The predicted surface response in accordance to response function as obtained from graph plotting of function f, the closness of fwill help in reaching to true results. The second order polynomial regression model was framed which results out to be:

$$Y = c_o + \sum_{i=1}^{n} c_i X_i + \sum_{i=1}^{n} b_{ii} X_i^2 + \sum c_{ij} X_i X_j \pm e_r$$

The following considerations of assumptions of surface roughness is often shown with linear, crossed and squared product terms of X_i's design finds the second-order response surface very precisely.

The second-order response surface representing the surface

roughness (Ra, lm) can be expressed as a function of cutting speed , depth of cut and feed rate.

$MRR = a_o + a_1 (A) + a_2(B) + a_3(C) + a_4(A^2) + a_5(B^2) + a_6(C^2) + a_7 (AB) + a_8(BC) + a_9(CA)$ $Ra = a_o + a_1 (A) + a_2(B) + a_3(C) + a_4(A^2) + a_5(B^2) + a_6(C^2) + a_7 (AB) + a_8(BC) + a_9(CA)$

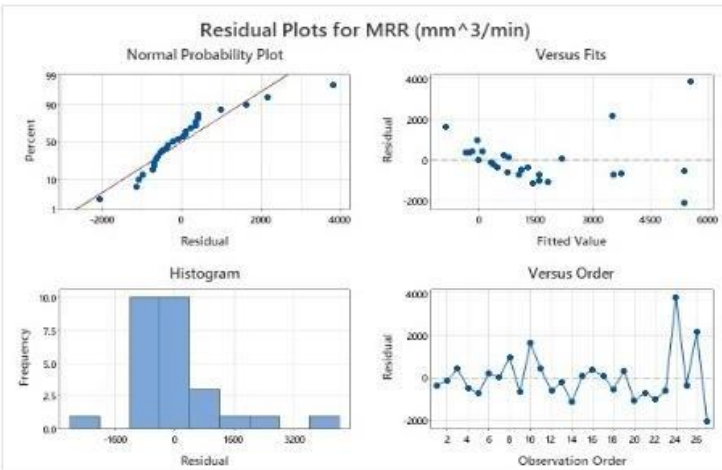
The following phase of documentation and experimentation saw the inclusion of machining parameters like depth of cut, feed rate and cutting speed on surface roughness and trials on included data sets were carried and machining on turning operation in dry condition was studied .

Here :

A = Cutting SpeedB = Feed Rate
C = Depth of Cut

7.2 Regression Analysis

The efficacy of desired optimality condition is obtained with the integration of regression analysis . The regression analysis makes the use of experimental data to calculate the equation coefficients which shows the study results system at any point in the experimentally range. The inclusion of regression analysis in output oriented machining parameters like feed rate, depth of cut andcutting speed was considered. By taking reference from Table 1 we have found out the coefficients for Material Removal Rate and Surface Roughness and hence find the regression equation for the above given parameters and if we put the input parameters viz. Cutting Velocity, Feed Rate, Depth of cut into the equation we will get the desired experimental Material Removal Rate and Surface Roughness and then compare it with the predicted values.



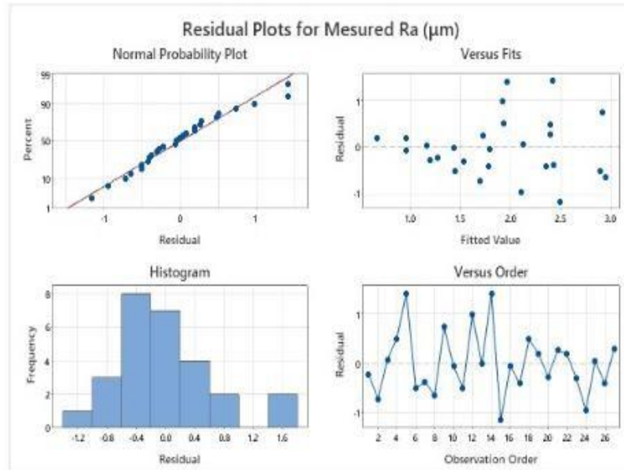


Fig.8 Residual Plots for MRR

Fig.9 Residual Plots for Ra

Regression Equation for Material Removal Rate (MRR):

MRR(mm^3/min) =-3250-21.72*A+ 50978 *B -2958 *C +0.01396 *A^2-96052* B^2-3983* C^2+ 19.0* A*B + 3847* B*C + 20.84 *A*C

Regression Equation for Measured Surface roughness (Ra):

Measured Ra(µm)= -1.16 +0.00175*A +12.8 feed rate*B +0.17 *C -0.000002 *A^2-10.8* B^2 +1.67* C^2-0.00578*A*B +1.67*B*C - 0.00578* A*B +1.9 *B*C + 0.00120 A*C

The computation and variance analysis was performed using ANOVA analysis where sums of squares and separated and then variance among these are checked due to different parameters and accordingly best fitted regression equation is formed..The ANOVA analysis terms were computed in accordance to MINITAB 21 calculation process flow. The design tree interface of ANOVA helped in data integration and regressive predicted values closure to statistically proven data sets.

In Fig.8 and Fig.9 residuals plot are shown for Material Removal Rate and Surface Roughness respectively. Normal Probability plot shows the fit of the distribution to the data and shows how the data is fitted along the distribution line. Versus Fits helps in verifying the random distribution and constant variance. Versus order plot helps in verifying that the residuals are independent fromone another and showing no particular pattern among the residuals.

7.3 Fitness Function

After finding coefficients for the regression equation from the Regression Analysis we got our fitness function for Material Removal Rate(MRR) and Surface Roughness(Ra). Fitness Function is very important in applying Genetic Algorithm Optimization. Fitness Function is the equation which is dependent on the inputs given for the desired outputs for e.g. Here are inputs are CuttingSpeed, Feed Rate, Depth of Cut and are output are Material Removal Rate and Surface Roughness. Fitness Function tells how goodor fit the data is according to the aims set for the outputs. Our output will be optimized on the basis of fitness function equation

Fitness Function for Material Removal Rate(MRR):

y(1) = -3250 - 21.72*x(1) + 50978*x(2) - 2958*x(3) + 0.01396*(x(1)^2) - 96052*(x(2)^2) - 3983*(x(3)^2) + 19.0*(x(1)*x(2)) + 3847*(x(2)*x(3)) + 20.84*(x(1)*x(3))

Fitness Function for Surface Roughness:
y(2) = -1.16 + 0.00175*x(1) + 12.8*x(2) + 0.17*x(3) - 0.000002*(x(1)^2) - 10.8*(x(2)^2) + 1.67*(x(3)^2) - 0.00578*(x(1)*x(2))+ 1.9*(x(2)*x(3)) + 0.00120*(x(1)*x(3))

8. Results of Optimization using GA

After developing fitness function we have defined the bounds for the inputs and population size were determined which was takenas 50. Tournament Selection was used and for the reproduction the crossover function was set to 0.6. Adaptive feasible function was used as the crossover function and Single point mutation function was used.
The upper and lower bounds for the input parameters are given below:

180 ≤ Cutting Speed ≤ 710

0.2 ≤ Feed Rate ≤ 0.4

0.2 ≤ Depth of Cut ≤ 0.6

Result for Material Removal rate and Surface Roughness obtained form genetic Algorithm is:

S.No	Material Removal Rate (mm^3/min)	Surface Roughness(μm)
1.	698.66	0.91

Table 3.Optimized Results from GA

The results obtained from genetic algorithm for Material Removal rate and Surface Roughness are summarized in the Table 4. Weobtained total of 18 optimized results out of which are criteria for selection was that Material Removal Rate should be maximum and for Surface Roughness was chosen to be less than equal to 1μm. The surface Roughness was chosen as per the industry requirements.

9. Conclusion

In our study the optimization of conventional turning operation were carried out with considerations of machining parameters like feed rate, cutting speed and depth of cut and optimal MRR was predicted , industrially viable using ANN and GA. For studying relationship between linearity of plots between actual and predicted , ANN model was developed and accuracy up to – were achievedon training and datasets. The model showed the closeness to input values and values pertaining to optimality was selected. The accounted error fall well within industrial limits were achieved. The integration of GA optimization led to calibrate targeted machining parameter suited index and achieve minimal loss of material finish compromise.

10. Future Scope

We are hopeful with successful integration of ANN- GA tools in being proactive prediction methodology , industrial machining parameters like nose radius, rake angle can be included for enhancement of current working process. The added advantage of computational contingent ability of process flowing complex machining ability and minimum machining time while considering technological and material constrains. The promising solutions to existing gap in behavioral prediction in intelligent machining and suitable solution for automatic selection of the
machining parameters may open new avenues to real time based manufacturing process optimization.
The design mode failure incorporation can be minimized upto greater extent and accuracy in desired manufactured product can beachieved leading to overall increase in productivity. The cycle time of failure and material enhancement can be viewed in real perspective.

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