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Multi Objective Evolutionary Optimization of Process Parameters in Turning Annealed Beryllium Copper Alloy

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ABSTRACT

This paper presents effective method and to determine optimal machining parameters in a turning operation on annealed Beryllium copper alloy to enhance the metal removal rate and minimize the surface roughness. The scope of this work is extended to Multi objective optimization. Response Surface Methodology is opted for preparing the design matrix. Artificial Neural Networks are used to train and validate the data prepared through experimentations. Multi Objective Genetic Algorithm is used for optimization of the performance measures of the process. A powerful model would be obtained with high accuracy to analyse the effect of each parameter on the output. The input parameters considered in this work are cutting speed, feed and depth of cut.

Introduction

In recent years, industrial producers and manufacturers have attempted to increase the efficiency, performance and accuracy of machining operations. These activities can be affected by a number of factors, such as machine tool conditions, tool geometry, work piece material and also machining parameters. Among these, machining parameters such as cutting speed, depth of cut and feed rate play a significant role in machining quality as parameters that are controlled by the user. Therefore, suitable selection of these parameters is necessary to reach optimal machining conditions in order to improve production efficiency.

So far, several researchers have performed experimental investigations about the machining operations and evaluated the effect of machining parameters on the outputs of the process. In fact, they have attempted to find suitable machining parameters in order to determine optimal conditions of the process. But, implementing numerous experimental tests for finding mentioned conditions is very time consuming and costly. To solve this problem, some of the researchers have attempted to model the machining processes by various methods such as, statistic, intelligent and analytical methods. Among them, predictive models are capable of estimating complex relationships between machining input parameters and corresponding outputs.

Literature review

Abdelouahhab Jabri, Abdellah El Barkany, Ahmed El Khalfi [1] presented a multi-optimization technique based on genetic algorithms to search optimal cuttings parameters such as cutting depth, feed rate and cutting speed of multi-pass turning processes. Two objective functions are simultaneously optimized under a set of practical of machining constraints, the first objective function is cutting cost and the second one is the used tool life time. Results obtained from Genetic Algorithms method are presented in Pareto frontier graphic. This technique allowed selecting optimal cutting parameters of a normal stat; other cutting parameters can be selected for different situation.

Somashekara and Lakshmana Swamy [2] studied on optimal setting of Turning parameters (Cutting speed, Feed and Depth of Cut) which results in an optimal value of Surface Roughness while machining Al 6351-T6 alloy with Uncoated Carbide Inserts. Several statistical modeling techniques have been used to generate models including Genetic Algorithm, Response Surface Methodology. In our study, an attempt has been made to generate a model to predict Surface Roughness using Regression Technique. Also an attempt has been made to optimize the process parameters using Taguchi Technique. S/N ratio and ANOVA analysis were also performed to obtain significant factors influencing Surface Roughness.

Aman Aggarwal and Hari Singh [3] made an attempt to review the literature on optimizing machining parameters in turning processes. Various conventional techniques employed for machining optimization include geometric programming, geometric plus linear programming, goal programming, sequential unconstrained minimization technique, dynamic programming etc. The latest techniques for optimization include fuzzy logic, scatter search technique, genetic algorithm, Taguchi technique and response surface methodology.

Scope of Study

The scope of the work is to embrace us about machine tool and the material that have to be cut and to the analysis. A model is developed for the selected performance measures (responses) namely: Metal Removal Rate and Surface Roughness 3.2 Material and Methodology.

Optimal Central Composite Design was used to design the experimental setting and the experiments were conducted on

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CNC Lathe with annealed Beryllium Copper alloy as work material. Out of 53 experiments as per the design, 40 were run (remaining 13 were kept aside for prediction purpose, which can be used for confirmation experiments) with speed, feed rate and depth of cut as cutting conditions to evaluate the metal removal rate and surface roughness while machining.

Artificial Neural Networks were used to test the significance of the experimental results. Response surface methodology is used to model the process and extract the optimal set of parameters.

Design of Experiments

Design of experiments is a powerful statistical analysis tool for modeling and analyzing the effect of process variables over performance variables which is an unknown function of these process variables. The selection of optimal points in the design space is generally called Design of Experiments.

The selection of the experimental design can have a good influence on the precision and the construction cost estimations. Randomly chosen design points make an inaccurate surface to be constructed or even prevent the ability to construct a surface at all. Many experimental design techniques have been used to aid in the selection of appropriate design points. In a factorial design factor range is divided into levels between the lowest and the highest values (Arbizu and Perez, 2003).

Experiments were conducted through the optimal Central Composite design method. In this work, the machining characteristics (speed, feed rate and depth of cut) are investigated based on metal removal rate and surface roughness. The machining parameters are tested for significance using the technique of analysis of variance obtained from regression analysis (Myers and Montgomery, 1995). Analysis of variance is used to study the effect of process parameters and establish correlation among the cutting speed, feed and depth of cut with respect to the major machinability factor, cutting forces such as cutting force and feed force.

The process variables with their ranges are listed in table 1 and table 2 gives the design matrix with output parameters.

Table 1. Process Variables with their Ranges

Factor	Name	Units	Minimum	Maximum
A	s	rpm	1175	1800
B	f	mm/min	145	400
C	d	mm	0.2	0.5

Artificial Neural Networks for validation of the model

Artificial Neural Networks are simplified models of biological nervous system inspired by the computing performed by a human brain. Kohonen (1987) defined neural network as "massively parallel interconnected networks of simple (usually adaptive) elements and their hierarchical organizations which are intended to interact with the objects of the real world in the same way as biological nervous system do." ANNs have the capabilit y to learn and thereby acquire knowledge and make it available for use. ANNs are built by connecting processing unit s, called nodes or neurons. Each of the input (xi) is associated with some weight (wi) which takes a portion of the input to the node for processing. The node combines the inputs (w) and produces net input which in turn is transformed into output with the help of transfer function/activation function.

The optimal network architecture was designed by means of MAT Lab Neural Network toolbox. Neurons in the input layer correspond to cutting speed (s), feed rate (f) and depth of cut (d). The output layer corresponds to metal removal rate (MRR) and surface roughness (Ra).

Table 2. Design matrix according to OCCD

Std	Run	A:s rpm	B:f mm/min	C:d mm	MRR mm^3/min	Ra microns
33	1	1331.25	336.25	0.425	38020	16.31
51	2	1643.75	272.5	0.425	41840	23.41
30	3	1643.75	336.25	0.275	49920	33.74
19	4	1800	272.5	0.5	47030	24.9
13	5	1800	145	0.35	33140	25.9
41	6	1487.5	208.75	0.275	29700	22.41
37	7	1487.5	208.75	0.35	29320	18.8
36	8	1643.75	272.5	0.35	42220	27.02
49	9	1487.5	208.75	0.425	28950	15.19
31	10	1331.25	208.75	0.425	23380	10.09
5	11	1175	145	0.5	10110	1.733
22	12	1800	272.5	0.35	47790	32.12
26	13	1487.5	272.5	0.5	35890	14.7
17	14	1487.5	145	0.5	21250	8.474
20	15	1487.5	400	0.5	50530	20.92
32	16	1643.75	208.75	0.425	34520	20.3
18	17	1175	272.5	0.5	24750	4.49
29	18	1331.25	336.25	0.275	38780	23.53
44	19	1643.75	272.5	0.275	42590	30.62
47	20	1331.25	336.25	0.35	38400	19.92
8	21	1800	400	0.5	61670	31.13
46	22	1487.5	336.25	0.275	44350	28.63
3	23	1175	400	0.2	40910	25.15
16	24	1800	400	0.35	62430	38.34
50	25	1331.25	272.5	0.425	30700	13.2
23	26	1487.5	145	0.35	22000	15.69
24	27	1487.5	400	0.35	51290	28.14
15	28	1175	400	0.35	40150	17.93
12	29	1800	272.5	0.2	48540	39.34
45	30	1643.75	208.75	0.35	34890	23.9
6	31	1800	145	0.5	32390	18.68
40	32	1487.5	272.5	0.425	36270	18.3
10	33	1175	272.5	0.2	26260	18.92
28	34	1643.75	208.75	0.275	35270	27.51
52	35	1487.5	336.25	0.425	43590	21.42
39	36	1487.5	272.5	0.275	37020	25.52
2	37	1800	145	0.2	33900	33.11
25	38	1487.5	272.5	0.2	37400	29.13
53	39	1487.5	272.5	0.35	36650	21.91
48	40	1643.75	336.25	0.35	49540	30.13
27	41	1331.25	208.75	0.275	24130	17.31
7	42	1175	400	0.5	39390	10.71
43	43	1331.25	208.75	0.35	23750	13.7
4	44	1800	400	0.2	63180	45.56
35	45	1331.25	272.5	0.35	31080	16.81
38	46	1487.5	336.25	0.35	43970	25.02
14	47	1487.5	400	0.2	52040	35.35
1	48	1175	145	0.2	11620	12.7
9	49	1487.5	145	0.2	22760	22.91
34	50	1643.75	336.25	0.425	49160	26.52
11	51	1175	145	0.35	10860	5.484
21	52	1175	272.5	0.35	25510	11.71
42	53	1331.25	272.5	0.275	31450	20.42

In this model, the inputs are fully connected to the outputs. In the neural network model, the output neurons on the input layer reach the jth neuron on the next layer and become its input as stated as in Equation (1).

$$net_j = \sum_{j=0}^{n} w_{ij} \qquad \text{------(1)}$$

Where

n is the number of neurons of the inputs to the j^{th} neuron in the hidden layer and net_j is the total or net input.

X_i is the input from the ith neuron in the preceding layer and w_{ij} is the weight of between the i^{th} neuron on the input layer and the jth neuron on the next layer.

A tangent hyperbolic function (f) that transforms the input value of the hidden layer to produce its output (out_j)

The back propagation algorithm

$$X_{k+1} = X_k \alpha_k g_k \quad \text{---------(2)}$$

The back propagation algorithm is used as learning procedure for multi layer perceptron network. The algorithm makes it possible to propagate error from the output layer to the input layer and correct the weight vectors, which will result in minimum error. The back propagation algorithm minimizes the square of the differences between actual output and desired output units and for all training pairs.

The error obtained when the training pair (pattern) consisting of both input and output given to the input layer of the network is given by equation (MSE).

$$MSE_p = \frac{1}{n}\sum_i \; (T_{pi} - O_{pi})^2 \quad \text{-------(3)}$$

where,

T_{pi} is the i^{th} component of the desired output vector;

O_{pi} is the calculated output of i^{th} neuron in the output layer.

Training Function and learning functions are mathematical procedures used to automatically adjust the network's weights and biases. The training function dictates a global algorithm that affects all the weights and biases of a given network. The activation function $f(x)$ is a non linear function and is given by

$$f(x) = a = tan\ sig(n) = 2/(1 + exp(-2 * n)) - 1 \quad \text{------ (4)}$$

Where $f(x)$ is differentiable.

Experimental results were used to develop an ANN model for predicting MRR and surface roughness. In this work, three inputs and two outputs are considered as the data of ANN model with input variables speed, feed rate and depth of cut and the output variables were MRR and Ra. The 32 results obtained from the experiments were used in training the network and 8 results were used for testing and 13 for validation. The summary of the network trained for MRR is given in table (3) for the architecture given in figure (1).

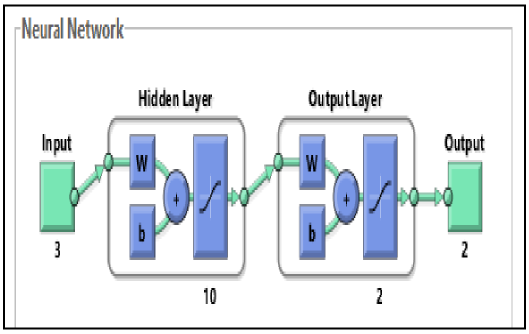

Figure 1. Network Architecture

Analysis of MRR

Table 3. Training and testing information for MRR network

Net Information	
Name	Net Trained on MRR
Configuration	Linear Predictor
Location	This Workbook
Independent Category Variables	0
Independent Numeric Variables	3 (A:s (RPM), B:f (mm/min), C:d (mm))
Dependent Variable	Numeric Var. (MRR(mm^3/min))
Training	
Number of Cases	32
% Bad Predictions (30% Tolerance)	0.0000%
Root Mean Square Error	2.761
Mean Absolute Error	2.455
Std. Deviation of Abs. Error	1.263
Testing	
Number of Cases	8
% Bad Predictions (30% Tolerance)	0.0000%
Root Mean Square Error	3.238
Mean Absolute Error	2.852
Std. Deviation of Abs. Error	1.533
Data Set	
Name	MRR
Number of Rows	40

13 experiments in the design matrix were first tested for prediction using the network model and confirmation tests were performed for testing the significance of the model. The last 13 rows in the table (4) show that the model is significant with minimum residual values. Graphical representation of performance of the neural network is represented in the figure (6). At epoch 17, the best performance is observed. The training state with gradient and validation check is given in the figure (7). Regression plots for the mean square error for trained, validated, test values and overall regression plot is shown in the figure (8). The R^2 values of 0.99 for all trained, validated, test and overall experimental runs prove the model validity. The same is represented in error histogram (figure 9).

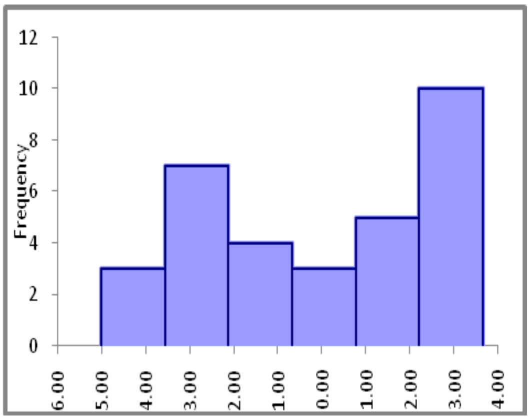

Figure 2. Histogram of residuals

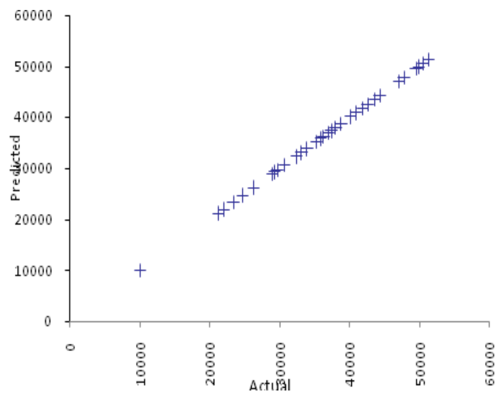

Figure 3. Predicted vs Actual MRR (training)

Table 4. Training report for MRR

				Train-Test-Predict Report for Net Trained on MRR			
A:s (RPM)	**B:f (mm/min)**	**C:d (mm)**	**MRR(mm^3/min)**	**Tag Used**	**Prediction**	**Good/Bad**	**Residual**
1331.25	336.25	0.425	38020	train			
1643.75	272.5	0.425	41840	train			
1643.75	336.25	0.275	49920	train			
1800	272.5	0.5	47030	train			
1800	145	0.35	33140	train			
1487.5	208.75	0.275	29700	train			
1487.5	208.75	0.35	29320	train			
1643.75	272.5	0.35	42220	train			
1487.5	208.75	0.425	28950	test	28947.03	Good	2.97
1331.25	208.75	0.425	23380	train			
1175	145	0.5	10110	test	10107.83	Good	2.17
1800	272.5	0.35	47790	test	47786.24	Good	3.76
1487.5	272.5	0.5	35890	train			
1487.5	145	0.5	21250	train			
1487.5	400	0.5	50530	train			
1643.75	208.75	0.425	34520	train			
1175	272.5	0.5	24750	train			
1331.25	336.25	0.275	38780	train			
1643.75	272.5	0.275	42590	test	42594.52	Good	-4.52
1331.25	336.25	0.35	38400	train			
1800	400	0.5	61670	train			
1487.5	336.25	0.275	44350	train			
1175	400	0.2	40910	train			
1800	400	0.35	62430	train			
1331.25	272.5	0.425	30700	train			
1487.5	145	0.35	22000	train			
1487.5	400	0.35	51290	train			
1175	400	0.35	40150	test	40151.11	Good	-1.11
1800	272.5	0.2	48540	train			
1643.75	208.75	0.35	34890	test	34894.71	Good	-4.71
1800	145	0.5	32390	train			
1487.5	272.5	0.425	36270	test	36268.87	Good	1.13
1175	272.5	0.2	26260	train			
1643.75	208.75	0.275	35270	train			
1487.5	336.25	0.425	43590	train			
1487.5	272.5	0.275	37020	test	37024.82	Good	-4.82
1800	145	0.2	33900	train			
1487.5	272.5	0.2	37400	train			
1487.5	272.5	0.35	36650	train			
1643.75	336.25	0.35	49540	train			
1331.25	208.75	0.275	*24130*	predict	24133.29		-3.29
1175	400	0.5	*39390*	predict	39395.16		-5.16
1331.25	208.75	0.35	*23750*	predict	23755.31		-5.31
1800	400	0.2	*63180*	predict	63185.86		-5.86
1331.25	272.5	0.35	*31080*	predict	31077.14		2.86
1487.5	336.25	0.35	*43970*	predict	43968.67		1.33
1487.5	400	0.2	*52040*	predict	52046.46		-6.46
1175	145	0.2	*11620*	predict	11619.73		0.27
1487.5	145	0.2	*22760*	predict	22759.13		0.87
1643.75	336.25	0.425	*49160*	predict	49160.40		-0.40
1175	145	0.35	*10860*	predict	10863.78		-3.78
1175	272.5	0.35	*25510*	predict	25507.44		2.56
1331.25	272.5	0.275	*31450*	predict	31455.12		-5.12

Table 5. Linear Function

	Intercept/Coefficient
Intercept	-45914.24
A:s (RPM)	35.65
B:f (mm/min)	114.85
C:d (mm)	-5034.97

Analysis of Surface Roughness

Table 6. Training and testing information for R_a network

Summary	
Net Information	
Name	Net Trained on Ra (2)
Configuration	Linear Predictor
Location	This Workbook
Independent Category Variables	0
Independent Numeric Variables	3 (A:s (RPM), B:f (mm/min), C:d (mm))
Dependent Variable	Numeric Var. (Ra(µ))
Training	
Number of Cases	32
Training Time	0.00.00
Number of Trials	0
Reason Stopped	Auto-Stopped
% Bad Predictions (30% Tolerance)	0.0000%
Root Mean Square Error	0.002583
Mean Absolute Error	0.002166
Std. Deviation of Abs. Error	0.001407
Testing	
Number of Cases	8
% Bad Predictions (30% Tolerance)	12.5000%
Root Mean Square Error	1.226
Mean Absolute Error	0.4361
Std. Deviation of Abs. Error	1.146
Prediction	
Number of Cases	13
Live Prediction Enabled	YES
Data Set	
Name	Ra
Number of Rows	53
Manual Case Tags	NO

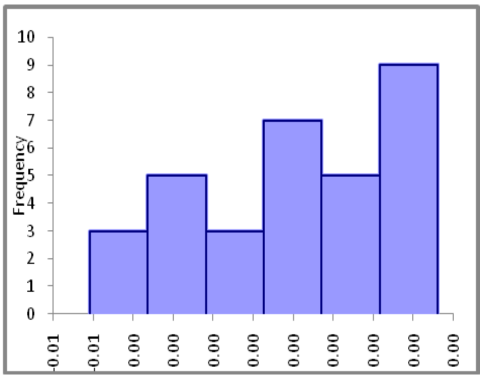

Figure 4. Histogram of Residuals for R_a (Training set)

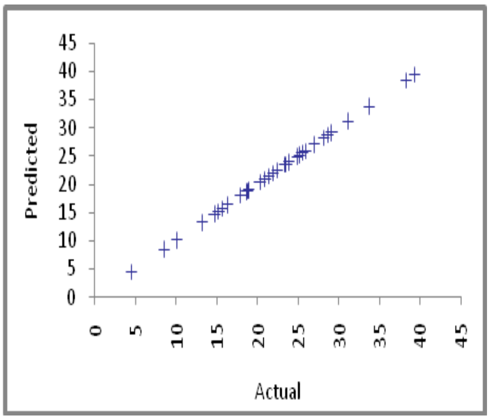

Figure 5. Predicted vs actual R_a (Training set)

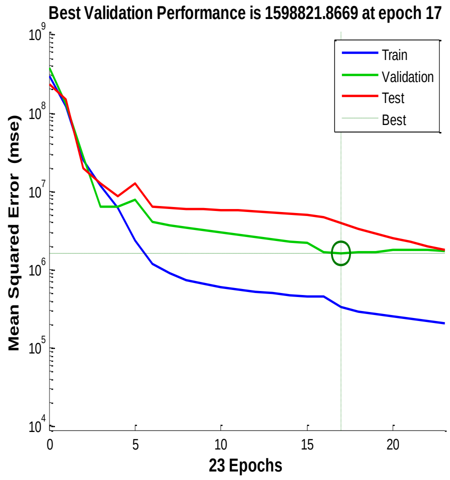

Figure 6. Performance Plot

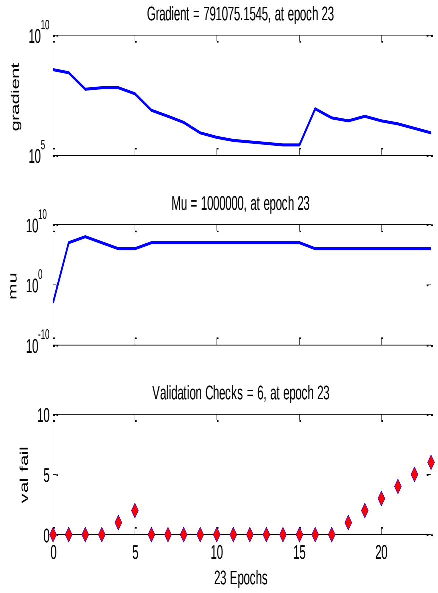

Figure 7. Training State

Table 7. Training report for R_a

				Train-Test-Predict Report for Net Trained on Ra			
A:s (RPM)	B:f (mm/min)	C:d (mm)	Ra(μ)	Tag Used	Prediction	Good/Bad	Residual
1331.25	336.25	0.425	16.31	train			
1643.75	272.5	0.425	23.41	train			
1643.75	336.25	0.275	33.74	train			
1800	272.5	0.5	24.9	train			
1800	145	0.35	25.9	train			
1487.5	208.75	0.275	22.41	train			
1487.5	208.75	0.35	18.8	train			
1643.75	272.5	0.35	27.02	train			
1487.5	208.75	0.425	15.19	train			
1331.25	208.75	0.425	10.09	train			
1175	145	0.5	1.733	test	-1.73	Bad	3.47
1800	272.5	0.35	32.12	test	32.12	Good	0.00
1487.5	272.5	0.5	14.7	train			
1487.5	145	0.5	8.474	train			
1487.5	400	0.5	20.92	train			
1643.75	208.75	0.425	20.3	train			
1175	272.5	0.5	4.49	train			
1331.25	336.25	0.275	23.53	train			
1643.75	272.5	0.275	30.62	test	30.63	Good	-0.01
1331.25	336.25	0.35	19.92	test	19.92	Good	0.00
1800	400	0.5	31.13	train			
1487.5	336.25	0.275	28.63	train			
1175	400	0.2	25.15	train			
1800	400	0.35	38.34	train			
1331.25	272.5	0.425	13.2	train			
1487.5	145	0.35	15.69	train			
1487.5	400	0.35	28.14	train			
1175	400	0.35	17.93	train			
1800	272.5	0.2	39.34	train			
1643.75	208.75	0.35	23.9	train			
1800	145	0.5	18.68	train			
1487.5	272.5	0.425	18.3	test	18.30	Good	0.00
1175	272.5	0.2	18.92	train			
1643.75	208.75	0.275	27.51	test	27.51	Good	0.00
1487.5	336.25	0.425	21.42	train			
1487.5	272.5	0.275	25.52	train			
1800	145	0.2	33.11	test	33.11	Good	0.00
1487.5	272.5	0.2	29.13	train			
1487.5	272.5	0.35	21.91	train			
1643.75	336.25	0.35	30.13	test	30.13	Good	0.00
1331.25	208.75	0.275	*17.31*	predict	17.31		
1175	400	0.5	*10.71*	predict	10.71		
1331.25	208.75	0.35	*13.7*	predict	13.70		
1800	400	0.2	*45.56*	predict	45.56		
1331.25	272.5	0.35	*16.81*	predict	16.81		
1487.5	336.25	0.35	*25.02*	predict	25.03		
1487.5	400	0.2	*35.35*	predict	35.35		
1175	145	0.2	*12.7*	predict	12.70		
1487.5	145	0.2	*22.91*	predict	22.91		
1643.75	336.25	0.425	*26.52*	predict	26.52		
1175	145	0.35	*5.484*	predict	5.48		
1175	272.5	0.35	*11.71*	predict	11.71		
1331.25	272.5	0.275	*20.42*	predict	20.42		
*R-Square (Training) = 0.999							

Table 8. Linear Function

	Intercept/Coefficient
Intercept	-23.14
A:s (RPM)	0.03266
B:f (mm/min)	0.04882
C:d (mm)	-48.11

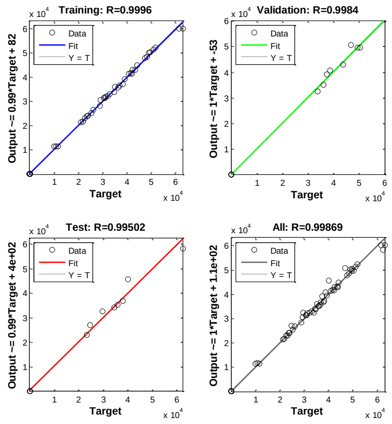

Figure 8. Regression Plot

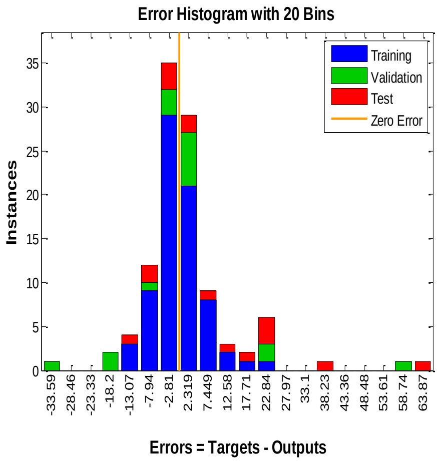

Figure 9. Error Histogram plot

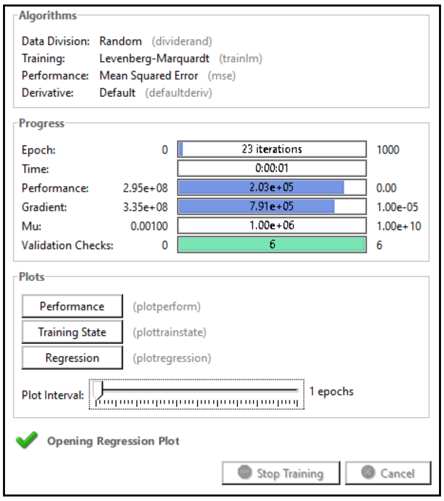

Figure 10. Training Process and Parameter Selection of Network

Optimization

The developed model through ANN is then used in genetic algorithm for setting the optimum values to maximize MRR an minimize surface roughness.

Genetic Algorithm (GA) is an evolutionary tool in solving optimization problems in engineering, mathematics and other fields. Global optimization is exposed as criteria in genetic algorithm. Best parents-best child through a number of generations are evolved out for getting global optimum outputs due to which it is an excellent optimization tool for complex problems.

GA tool in MATlab is utilized for its simplicity and efficiency for solving the present problem imported from NN tool. Figure (11) shows the optimization criteria.

The objective functions for MRR and R_a are written in M-file in MATLAB as

function y = ga1(x)

y(1) = 63180-(-45912.2+35.6466*x(1)+114.848*x(2)-5034.07*x(3));

y(2) = -23.961572358169+0.032330913710112 * x(1) +0.042410486223248*x(2)-34.602836037421 *x(3);

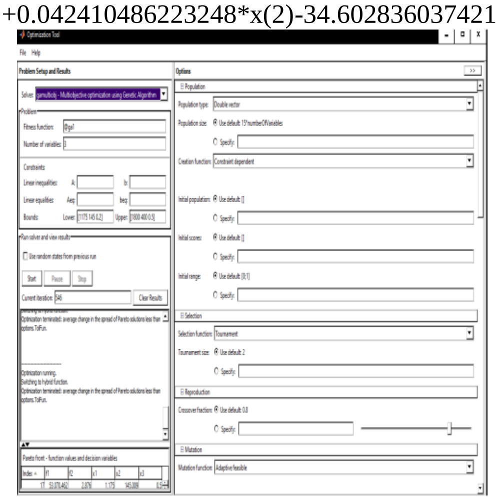

Figure 11. Running Process of Optimization Tool Box in MATLAB

Here, y(1) represents MRR for maximization and y(2) represents R_a for minimization. x(1), x(2), x(3) represent the input parameters speed, feed rate and depth of cut. When the above function is exported and run on MOGA tool box, the pareto front plot with best individuals can be obtained as in the figure (12). The optimal set of the input and output parameters are tabulated in the table (9).

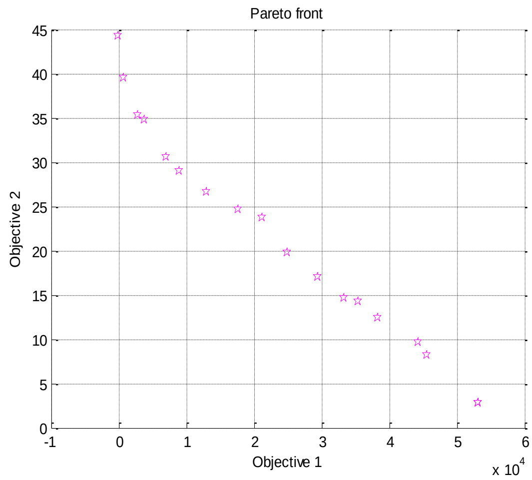

Figure 12. Pareto Front

Result and Conclusion

The mathematical function for turning process parameters of annealed Beryllium copper alloy has been obtained and validated with neural network modelling, which is applied in multi objective Genetic Algorithm for optimizing the process parameters and is given in Table (9). A satisfactory value has been obtained which was proven with confirmatory test with 98% confidence level.

Table 9. Optimal setup of parameters

Speed (RPM)	Feed rate (mm/min)	Depth of cut (mm)	MRR (mm^3/min)	R_a (µ)
1175	145	0.5	53070.462	2.87

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