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Experimental Investigation and Optimization of Response Parameters in Cylindrical Grinding of EN24 Steel using Artificial Neural Network and Grey Relational Analysis

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Abstract: External cylindrical grinding is a type of grinding process which is used to grind the cylindrical objects like engine shafts, connecting rods, spindles, axles etc. In the present work an experimental investigation is carried out to find the effect of control parameters on response parameters and EN24 alloy steel is selected for machining on cylindrical grinding machine. Material removal rate and surface roughness are taken as response parameters while workpiece speed (v), feed rate (f), depth of cut (d) are selected as control parameters. Taguchi DOE is used with L16 orthogonal array for optimum combination of control parameter levels, after that experiments are conducted on cylindrical grinding. By using artificial neural network technique a model has been developed for validation and prediction of cylindrical grinding response parameters. In order to train the network experimental data has been used and comparison of ANN predicted data with actual data is also done. The combined and optimized result for multi-response parameters of Ra and MRR is achieved by grey relational analysis.

Keywords — Artificial neural network (ANN), Cylindrical grinding, Material removal rate (MRR), Surface roughness (Ra), Taguchi method, Grey relational analysis (GRA).

I. INTRODUCTION

Quality, dimensional accuracy, productivity with minimum cost and low material wastage are the basic requirements of manufacturing industries. In order to fulfill these requirements all manufacturing industries use different machining methods and methodologies. Grinding is a suitable material removal process for hard materials for required surface finish and greater tolerance.

Cylindrical grinding is a process which is used to grind the cylindrical work pieces and removes the material in the form of small chips. Cylindrical grinding process can produce a high quality surface finish with excellent accuracy and to very close tolerance. In cylindrical grinding process the work piece is held between two centers and by the help of grinding wheel the grinding operation is performed. Various applications for cylindrical grinding process are to sizing of hardened axles and transmission shafts, finishing bearing diameters and seal surfaces, finish grinding hard chromed hydraulic cylinder shafts and hard faced retainer pins etc.

The various process and response parameters of cylindrical grinding are Grinding wheel speed, Work piece speed, Feed rate, Depth of cut, Material removal rate, Surface roughness, Coolant or grinding fluid flow rate, Size and hardness of abrasive particles.

II. LITERATURE SURVEY

The literature survey includes research papers related to cylindrical grinding process which was used for machining of different materials like EN15AM Steel, C40E Steel, 304 Stainless Steel, EN 19, EN 31, Alloy steels on different machining conditions. These papers also define the current research trends in cylindrical grinding process. The following papers highlight the use of different input process parameters and use of different methodologies like ANN, ANOVA, Taguchi, GRA, RSM, etc.

Sandeep Kumar et. al [1] used grey relational analysis (GRA) to optimize the process parameters of cylindrical grinding on EN8 steel alloy. Grinding wheel speed, workpiece speed, feed rate and depth of cut selected as process parameters and Ra, MRR were the output parameters. Total 9 experiments carried out and by the help of grey relational analysis (GRA) optimum combination of process parameters achieved. Workpiece speed and table feed were the most effective parameters for MRR and grinding wheel speed, depth of cut were most significant parameters for Ra. N Sudheer Kumar Verma et. al [2] found the effect of workpiece speed, depth of cut and feed rate on

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the material removal rate and surface roughness of Inconel 800 alloy in cylindrical process. Total 27 experimental data are conducted by the help of full factorial design considering 3 levels for each parameter during the machining process. Results from experiments are used for training the regression models, neural networks and adaptive-neuro fuzzy interface system (AFNIS). It was observed Ra decreases if increase in workpiece speed and depth of cut but increases if increase in feed rate. Similarly MRR decreases by increasing in workpiece speed but increase if increase in depth of cut and feed rate. M. Ganesan et. al [3] selected cutting speed, feed rate and depth of cut as input parameters and find out the effect of these parameters on Ra of 304 stainless steel by using 9 specimen rods of 20 mm diameter and 100 mm length each. Author selected taguchi design of experiments of L9 orthogonal array with 3 different levels and 3 different factors. In order to determine most effective input parameters for the response parameters ANOVA (Analysis of Variance) is used. Ravi Kumar Panthangi et. al [4] selected three different alloys i.e. EN19, EN24, EN31 alloy steels of different hardness. The main reason of author to select three different alloys was to find out the effect of input process parameters material hardness, workpiece speed and depth of cut on surface roughness in cylindrical grinding. Experiments are performed in the order given by taguchi method as per L9 orthogonal array. The experiment results are used in Matlab software and genetic algorithm was applied to find the optimum values. Author found that hardness has a major effect on Ra. Saikat Chatterjee et. al [5] investigated the significance of process parameters on aluminum bronze material in cylindrical traverse cut grinding process. The Ra data is analyzed by S/N ratio and graphical presentation in Minitab. It was found that longitudinal feed is the most significant factor for Ra and workpiece speed is the least significant factor. Kshitij R Patil et. al [6] found the effect of workpiece speed, feed rate, hardness of the material and depth of cut on EN19 steel alloy in cylindrical grinding process. Taguchi method with L9 orthogonal array used as design of experiments. Optimum parameters are founded by the help of mathematical modeling. The conclusion was increase in feed rate and depth of cut increases the MRR but increase in hardness decreases MRR. Similarly Ra decreases with increase in hardness and workpiece speed but Ra increases with increase in depth of cut and feed rate. Tushar Khule et. al [7] selected AISI 304 steel alloy and found the effect of workpiece speed, feed rate and depth of cut on MRR and Ra. Taguchi method with regression analysis and ANOVA techniques were used for optimum results. The most effective parameter for Ra was workpiece speed of 750 m/min and other optimum values were feed rate of 3 m/min and 10.5 μm of depth of cut. Ramesh Rudrapati et. al [8] found the effect of infeed, longitudinal feed and workpiece speed on Ra and vibration in Cylindrical grinding of cold rolled stainless steel of SS410 grade. Author used Box-Behnken design matrix and response surface methodology to find out the relation between input and output parameters and multi-objective genetic algorithm was used for optimum result. For Ra the most significant parameters were longitudinal feed and workpiece speed. M. Melwin Jagadeesh Sridhar et. al [9] used OHNS steel for cylindrical grinding and found the effect of number of passes, depth of cut and workpiece speed on Ra and tool wear. The experiments conducted over L9 orthogonal array with 3 different levels. S/N ratio and ANOVA techniques used to optimization and analyze the result. It was found that workpiece speed was the most dominating parameter for Ra. For minimum Ra the optimum values of parameters was 150 rpm of work speed, 1 number of pass and 0.02 mm depth of cut.

III. EXPERIMENTAL DETAILS

A. Experimental Setup

In the present research EN24 steel alloy is used as workpiece material. The EN24 alloy steel is widely used for various industrial purposes like high strength shafts, punches, dies, bolts, studs, screws, rollers etc. and in automobile sector like gears, heavy duty axles, connecting rods etc.[10] Total 16 cylindrical bars of EN24 steel is selected as workpiece having diameter of 30 mm and length of 120 mm as shown in figure 1.

Figure 1: Workpieces

The experiments were conduct on an external cylindrical grinding machine BPI-300 (Bharat Products India). The range of control factors for the selected machine is shown in table 1.

Table 1: Range of Parameters

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S. No.	Parameters	Units	Range
1	Workpiece Speed (V)	RPM	40 – 160
2	Feed Rate (*f*)	mm/min	30– 120
3	Depth of Cut (*d*)	mm	0.01 – 1

B. Design of Experiments

Taguchi recommends the use of orthogonal array. A machining process is easily analyzed with the help of orthogonal array. It includes control factors and combinations of their levels. If experiments are conducted according to orthogonal array then it is easy to find out effects of control factors on response factors and effect of noise factors also minimized. Orthogonal array is selected on the basis of control factors and their levels. For present work L16 orthogonal array is used. Properties of L_{16} OA are as follows:

No. of experiments = 16

No. of levels = 4

No. of factors = 4

Table 2: Control Factor Levels

Control factors	Units	Levels			
		i	ii	iii	iv
v	RPM	40	80	120	160
f	mm/min	30	60	90	120
d	mm	0.02	0.04	0.06	0.08

Minitab-17 software is used to for DOE. The combination of parameters is shown in table 3.

Table 3: Combinations of Input Parameters

Exp.	V	d	f
1.	40	0.02	30
2.	40	0.04	60
3.	40	0.06	90
4.	40	0.08	120
5.	80	0.02	60
6.	80	0.04	30
7	80	0.06	120
8.	80	0.08	90
9.	120	0.02	90
10.	120	0.04	120
11.	120	0.06	30
12.	120	0.08	60
13.	160	0.02	120
14.	160	0.04	90
15.	160	0.06	60
16.	160	0.08	30

C. Experimental Observation

Total 16 cylindrical bars of EN24 steel is selected as workpiece, initially the turning operation was performed on each and every specimen with the help of lathe machine. The specimens are marked numbers from 1 to 16 so that the experiment can be conducted by L16 orthogonal array. The experiments were conducted according to the combinations shown in table 3. A surface roughness tester of series SURTRONIC S-128 is used for measurement of surface roughness. For Material removal rate the weight of specimen is measure by weighting machine before and after the machining process and time is measure by stop watch for each experiment. After it MRR is obtained by dividing the difference of weight before and after machining process by total machining time.

IV. RESULT AND DISCUSSIONS

From the experimental data it is found that maximum MRR 0.5588 g/sec is obtained at 160 rpm of workpiece speed, 0.02 mm of depth of cut and 120 mm/min of feed rate. Similarly minimum Ra 0.5933 µm is obtained at 40 rpm of workpiece speed, 0.02 mm of depth of cut and 30 mm/min of feed rate.

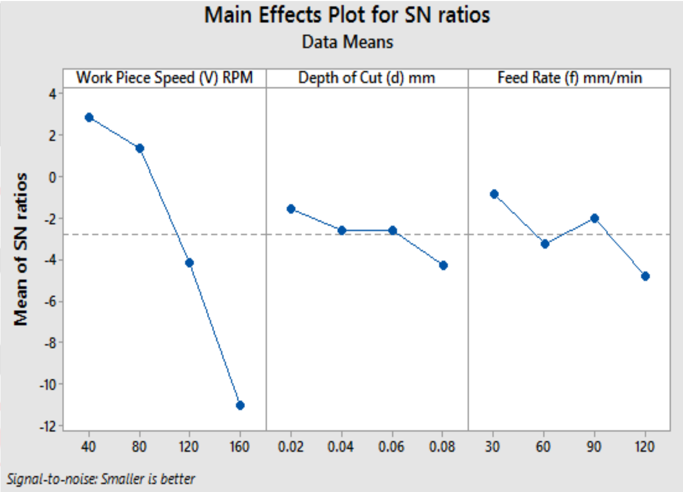

Figure 2: MRR Vs Process Parameters

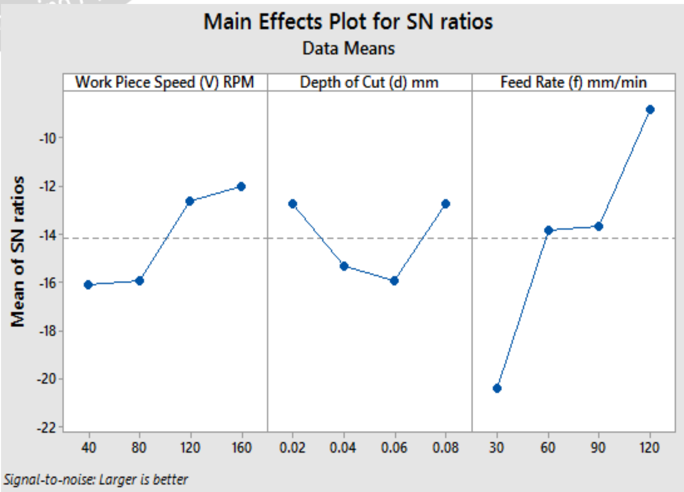

Figure 3: Ra Vs Process Parameters

Main effect plot shows that for MRR and Ra the workpiece speed and feed rate are the most effective parameters. Increase in workpiece speed and feed rate increases MRR and increase in depth of cut decreases MRR.

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V. Development of Artificial Neural Network and Grey Relational Analysis

A. Artificial Neural Network

Artificial neural network is a set of programming codes which is inspired by biological nervous systems. Some processing elements called artificial neurons are interconnected with each other and make a network called artificial neural network. Neural networks are able to process the information's in same way as the human brain processes information. [11] Types of ANN are as below:

a. Feed-Forward Network
b. Feed-Back Network

Mathematically an artificial neural network can be define as

$$u_k = \sum_{j=1}^{m} w_{kj}\, x_j$$

Where,

u_k = Total inputs in a neuron
x_j = Inputs = $x_1, x_2, x_3, \ldots\ldots x_m$
w_{kj} = Weights = $w_{k1}, w_{k2}, w_{k3}, \ldots\ldots w_{km}$

$$y_k = \varphi(u_k + b_k)$$

Where,

y_k = Output of neuron
b_k = Bias
φ = Transfer function [12]

The ANN is developed in MATLAB R2017a software. Artificial neural network learn with the help of examples. There are three types of learning adopted by ANN, which are as follows:

a. Supervised Learning
b. Unsupervised Learning
c. Reinforcement Learning [13]

In the present work ANN is used for estimation and prediction of cylindrical grinding response parameters. With the use of ANN it is easy to predict the surface roughness and material removal values. In order to train and test the model experimental data is used. Steps for ANN:

Step-1 Collection of data from experiments
Step-2 Preparation of database
Step-3 Training of neural network
Step-4 Selection of parameters for ANN model
Step-5 Result of ANN

After the development of ANN model it is found that the ANN predicted values are more than 95% similar to the experimental values which show the authentication of the present work. The predicted values of experiment results are obtained by ANN and the difference between actual data and ANN predicted data is shown in figure 4 and figure 5. According to the figure 4 out of 16 experimental values only three experimental values are different from ANN predicted values. This shows the accuracy of the present work. Experiment number 2, 5 and 14 have the different experimental and ANN values. Similarly according to the figure 5 Only three experimental values are differing from predicted values and remaining all thirteen values are same as predicted values.

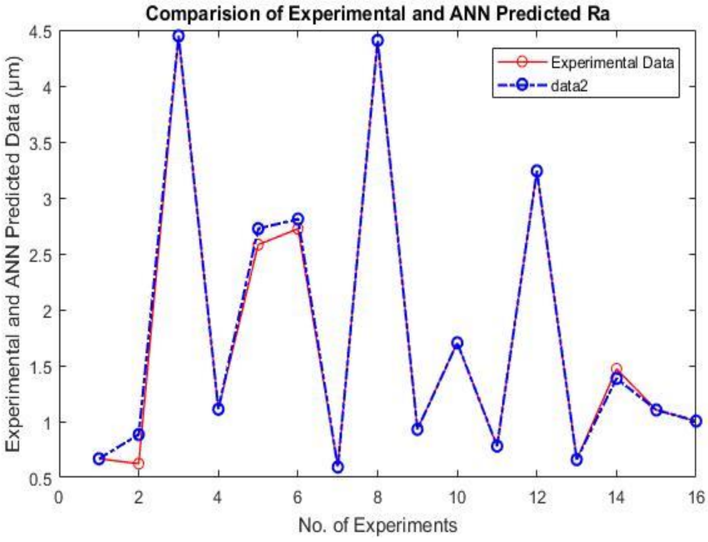

Figure 4: Experimental and ANN predicted Ra

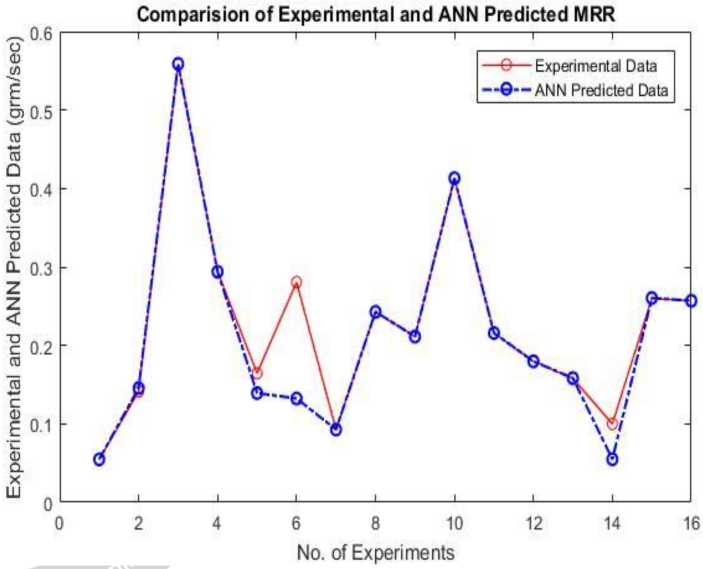

Figure 5: Experimental and ANN predicted MRR

B. Grey Relational Analysis

Grey relational analysis (GRA) is generally used for optimization of multiple performance parameters. In Grey system theory the term 'Grey' means uncertain or incomplete information, so GRA can handle unclear problems and incomplete problems very precisely. [14] The various steps for GRA are as below:

Step-1 Normalize the experimental results

Larger-the-better

$$x_i^*(k) = \frac{x_i(k) - \min x_i(k)}{\max x_i(k) - \min x_i(k)}$$

Where,

i = Number of experimental data =1,2,3………m
k = Influence factor =1,2,3………m
$x_i(k)$ = Original sequence
$x_i^*(k)$ = Sequence after data preprocessing
max $x_i(k)$ = Largest value of $x_i(k)$
min $x_i(k)$ = Smallest value of $x_i(k)$ [15]

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This normalization formula is used where response is to be maximized like MRR.

Smaller-the-better

$$x_i^*(k) = \frac{\max x_i(k) - x_i(k)}{\max x_i(k) - \min x_i(k)}$$

This normalization formula is used where response is to be minimized like Surface roughness (Ra). [15]

Step-2 To find deviational sequence

From the normalized values deviation sequence can be found out by following formula

$$\Delta x_i(k) = |x_o(k) - x_i(k)|$$

Where,

$x_o(k)$ = Maximum normalized value

Step-3 Calculation of grey relational coefficient

After the deviational sequence the grey relational coefficient can be calculated as below

$$\xi_i(k) = \frac{\Delta\min + \xi\Delta\max}{\Delta x_i(k) + \xi\Delta\max}$$

Where,

ξ_i (k) = Grey relational coefficient in sequence

Δmin = Minimum value of deviational sequence

Δmax = Maximum value of deviational sequence

ξ = Identification or distinguishing coefficient

The value of ξ ranges between 0 to 1 and if all the parameters are given equal preference then it is taken as 0.5. [15]

Step-4 To find out grey relational grade

Grey relation grade is obtained by taking the average of grey relational coefficients.

$$\gamma_i = \frac{1}{n}\sum_{k=1}^{n} \xi_i(k)$$

Where,

n = Total number of experiments [16]

Step-5 Assign ranking for grey relational grades

In this step we have to assign the ranks to the grey relational grades. The higher value of grey relational grade will get the first rank and the lower valve will get last rank.[17]

As from table 4 it is clear that the experiment number 2 gets the first rank so it is the optimized combination of parameters. The optimized combinations of input parameters for response parameters are workpiece speed (v) of 40 rpm, depth of cut (d) of 0.04 mm and feed rate (f) of 60 mm/min.

Table 4: Grey Relational Analysis

No. of Exp.	Normalized Data		Deviation Sequence		Grey Relational Coefficient		Grade	Rank
	MRR	Ra	MRR	Ra	MRR	Ra		
1	0.0755	1.0000	0.9245	0.0000	0.3510	1.0000	0.6755	2
2	0.2054	0.9827	0.7946	0.0173	0.3862	0.9665	0.6764	1
3	0.1803	0.9246	0.8197	0.0754	0.3789	0.8690	0.6239	11
4	0.4745	0.8658	0.5255	0.1342	0.4876	0.7884	0.6380	7
5	0.3196	0.9515	0.6804	0.0485	0.4236	0.9116	0.6676	3
6	0.0000	0.9809	1.0000	0.0191	0.3333	0.9633	0.6483	5
7	0.4080	0.8677	0.5920	0.1323	0.4579	0.7908	0.6243	10
8	0.3105	0.9127	0.6895	0.0873	0.4203	0.8514	0.6359	8
9	0.4010	0.8934	0.5990	0.1066	0.4550	0.8243	0.6396	6
10	0.7109	0.7119	0.2891	0.2881	0.6337	0.6345	0.6341	9
11	0.0005	0.7946	0.9995	0.2054	0.3334	0.7088	0.5211	12
12	0.1540	0.4248	0.8460	0.5752	0.3715	0.4650	0.4182	14
13	1.0000	0.0000	0.0000	1.0000	1.0000	0.3333	0.6667	4
14	0.3732	0.0104	0.6268	0.9896	0.4437	0.3357	0.3897	16
15	0.2479	0.3132	0.7521	0.6868	0.3993	0.4213	0.4103	15
16	0.1677	0.4472	0.8323	0.5528	0.3753	0.4749	0.4251	13

VI. CONCLUSION

The present research work involves the development of an ANN and GRA model to measure the surface roughness and material removal rate in cylindrical grinding process of EN24 steel. The proposed neural network modeling is found easy and promising technique to develop predictive model for mapping input and output parameters. The investigation indicates that the process parameters workpiece speed, feed rate and depth of cut are the primary influencing factors which affect the surface roughness and MRR. The GRA revealed that the optimized values of Ra is 0.66 µm and MRR is 0.1582 g/sec obtained at workpiece speed (v) of 40 rpm, depth of cut (d) of 0.04 mm and feed rate (f) of 60 mm/min.

VII. FUTURE SCOPE

The work can be extended by considering different parameters like grinding wheel speed, coolant flow rate, number of passes etc. Cylindrical grinding process can be extended further, by selecting other materials or steel alloys.

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REFERENCES

[1] Sandeep Kumar, Dr. S. Dhanabalan, Dr. C. Sathiya Narayanan, "Multi-Parametric Optimization of Universal Cylindrical Grinding Using Grey Relational Analysis", International Journal of Ethics in Engineering & Management Education, vol.-5, no.-3, pp. 12-18, March 2018

[2] N Sudheer Kumar Varma, I R P K Varma, S Rajesh, K Sita Rama Raju, V V Murali Krishnam Raju, "Prediction of Surface Roughness and MRR in Grinding Process on Inconel 800 Alloy using Neural Networks and ANFIS", International Conference of Materials Processing and Characterization, pp. 5445–5451, 2018

[3] M. Ganesan, S. Karthikeyan, N. Karthikeyan, "Prediction and Optimization of Cylindrical Grinding Parameters for Surface Roughness Using Taguchi Method, "Journal of Mechanical and Civil Engineering", pp. 39-46, 2017

[4] Ravi Kumar Panthangi, Vinayak Naduvinamani, "Optimization of Surface Roughness in Cylindrical Grinding Process", International Journal of Applied Engineering Research, vol.-12, no.-18, pp. 7350-7354, 2017

[5] N Sudheer Kumar Varma*, S Rajesh, K Sita Rama Raju, V V Murali Krishnam Raju, "Neural Network and Fuzzy Logic Based Prediction of Surface Roughness and MRR in Cylindrical Grinding Process", International Conference on Advancements in Aeromechanical Materials for Manufacturing, pp. 8134–8141, 2017

[6] Saikat Chatterjee, ,Ramesh Rudrapati,Pradip Kumar pal,Goutam Nandi, "Experiments, Analysis and Parametric Optimization of Cylindrical Traverse Cut Grinding of Aluminium Bronze" International Conference of Materials Processing and Characterization, pp. 5272–5280, 2018

[7] Kshitij R Patil, Rupesh J Karande, Dadaso D. Mohite, Vishwas S Jadhav, "Modeling and Optimization of Cylindrical Grinding Parameters for MRR and Surface Roughness", International Journal of Engineering Sciences & Research Technology, pp. 498-503, April 2017

[8] Aman thakur, Dr. V.Sahni, "Optimization of Traverse Cut Cylindrical Grinding Process Parameters of Heat Treated EN-8 Steel", International journal of Advance Research in Science and Engineering, vol-6, no.-12, pp 1512-1523, December 2017

[9] Tushar Khule, Prof. Mali M.S., Dr.Zope S.B., "Surface Grinding Parameters Optimization of Austenitic Stainless Steel Sheet (AISI 304) by Taguchi Method", International Journal of Scientific Research in Science, Engineering and Technology vol.- 3, no.-5, pp. 379-384, August 2017

[10] Aparna devi.I, Sudhakar.I, V.S.N. Venkata Ramana, "An Experimental Study on Corrosion Behavior of EN8 and EN24 Grade Steels, *4th International Conference on Materials Processing and Characterization*, pp. 1251-1256, 2015

[11] Sakshi Kohli, Surbhi Miglani, Rahul Rapariya, "Basics of Artificial Neural Network", *International Journal of Computer Science and Mobile Computing*, vol.-3, no.-9, pp. 745-751, September 2014

[12] Tripti Rani Borah, Kandarpa Kumar Sarma, Pranhari Talukdar,"Biometric Identification System Using Neuro and Fuzzy Computational Approaches", *A Volume in the Advances in Computational Intelligence and Robotics*, pp. 336-366, December 2015

[13] Erdi Tosun, Kadir Aydin, Mehmet Bilgili, "Comparison of Linear Regression and Artificial Neural Network Model of a Diesel Engine Fueled with Biodiesel-Alcohol Mixtures", *Alexandria*

[14] Shouyi Wang, Robert Babuska, "Machine Learning Algorithms in Bipedal Robot Control", *IEEE Transactions On Systems, Man, And Cybernetics-Part C: Applications And Reviews*, vol.-42, no.-5, pp. 728-743, September 2012

[15] Ninoslav Slavek, Alan Jovic, "Application of Grey System Theory to Software Projects Ranking", *Journal for Control, Measurement, Electronics, Computing and Communications*, pp. 284–293, 2012

[16] Amlana Panda, Ashok Kumar Sahoo, Arun Kumar Rout, "Multi-Attribute Decision Making Parametric Optimization and Modeling in Hard Turning Using Ceramic Insert Through Grey Relational Analysis: A Case Study", *Decision Science Letters*, pp. 581-592, March 2016

[17] C. L. Lin, "Use of the Taguchi Method and Grey Relational Analysis to Optimize Turning Operations with Multiple Performance Characteristics", *Materials and Manufacturing Processes*, vol.-19, no.-2, pp. 209–220, 2004

 DOI : 10.18231/2454-9150.2019.0036