Available online at www.sciencedirect.com

ScienceDirect

Materials Today: Proceedings 5 (2018) 6645–6654

materialstoday: PROCEEDINGS

www.materialstoday.com/proceedings

IMME17

Application of Grey-Fuzzy Approach for Optimization of CNC Turning Process

D. Palanisamy*, P. Senthil

Department of Production Engineering, National institute of Technology, Tiruchirappalli - 620 015, India.

Abstract

This present investigation details the determination of optimum machining conditions for turning of PH stainless steel by grey fuzzy approach which is a fast and effective optimization technique having combinatorial advantages of both grey system and fuzzy logic approach. Taguchi's design of experiment method is employed for designing and an L27 orthogonal array is selected for performing the experiments. The cutting speed, feed rate and depth of cut are considered as input variables. The surface roughness and power consumption are deemed as performance characteristics. Taguchi based grey system approach and grey-fuzzy grade are used to evaluate the relationship between input variables and performance measures. To convert the multi-quality characteristics into a single performance index, the fuzzy inference system is used. It is proved from the investigation that the proposed method of optimization technique improves the multi performance characteristics effectively.

Selection and/or Peer-review under responsibility of International Conference on Emerging Trends in Materials and Manufacturing Engineering (IMME17).

Keywords: PH stainless steel; Grey-Fuzzy; CNC machining; Power consumption; Surface Roughness

1. Introduction

15-5 is a precipitation hardenable stainless steel exhibits good combination of high strength and hardness, with excellent corrosion resistance and weldability and has the property of high resistance to crack propagation, good transverse properties and good resistance to stress-corrosion cracking.

* Corresponding author. Tel.:+91 8754152845
E-mail address: dpalanisamy.me@gmail.com

Selection and/or Peer-review under responsibility of International Conference on Emerging Trends in Materials and Manufacturing Engineering (IMME17).

This material is extensively used in many applications to withstand high pressure and corrosive environment. Machining can be done on 15-5PH stainless steel alloy at any obtainable condition due to its ductile property. Compared with the other PH steels, 15-5PH provides dimensional stability and better polishability [1, 2].

The importance of predicting surface integrity of 15-5 Precipitated hardening stainless steel was reported which makes more attention in nuclear applications [3]. Ashok kumar et al. [4] reported that15-5 PH steel is predominant than 17–4 PH stainless steel. In the solution treated condition this material can be machined at the rate similar to SS 304, and these machining rates fit well for about 60 percentage with H900 condition. Ross [5] focused and used Taguchi method to optimize the process parameters in achieving high quality products. Optimization using Taguchi method is concerned with single performance characteristic [6]. Optimising multiple response characteristics is more difficult compared with single performance characteristics [7, 8]. Carmita Camposeco-Negrete [9] made an attempt to optimize turning parameters while machining AISI 6061 T6 under rough condition to minimise energy consumption. The influencing factor was determined using orthogonal array, signal to noise (S/N) ratio and analysis of variance (ANOVA).

Ashok Kumar and Swastik Pradhan [10] examined the influence of process parameters using Taguchi method on different parameters. ANOVA and least square method were used in adopting regression analysis in predicting output characteristics [10]. Raj Mohan et al. [11] used grey-fuzzy algorithm to find the optimal machining parameters in drilling of aluminium metal matrix composites. The new proposed method was coupled with both the grey relational analysis with the fuzzy logic and obtained a grey-fuzzy reasoning grade in evaluating the multiple performance characteristics. Issam Hanafi et al. [12] used classical response surface regression Technique and implemented fuzzy logic model to predict the relationship between the machining input variables cutting speed, feed rate and depth of cut with cutting power, cutting force and cutting pressure.

Sarojrani Pattnaik et al. [13] determined the optimal process parameters with multiple performance characteristics in the investment casting process using orthogonal array with grey–fuzzy logic and grey fuzzy reasoning grade to analyse the performance index in determining the process parameters. Anil Gupta et al. [14] described about the Taguchi method, fuzzy technique and fuzzy logic in optimising CNC turning parameters with multiple response characteristics. Fuzzy reasoning for the multiple response characteristics was performed and found that the performance characteristics have been improved.

Chakradhar and Venugopal [15] identified the best combination of process variables in electrochemical machining of EN-31 steel by using grey relational analysis. Bala Murugan et al. [16] used grey relational analysis to optimize the hard machining parameters. Asokan et al. [17] applied grey relational analysis and calculated the grey grade to optimise the multi-objective model. To evaluate the relationship between input and output parameters ANN model and multiple regression models have been developed. The percentage deviation between the experimental grade and predicted grade is determined. Abdellatif Khamlichi et al. [18] used grey relational theory and Taguchi based optimization technique to optimize the parameters in achieving minimum power consumption and better surface quality. Parida and Pal [19] used Grey-Fuzzy Taguchi technique to optimize the parameters of Friction Stir Welding process with eight input parameters and five responses. Based on the above literature review it is found that limited work has been done using Grey –fuzzy to optimize turning parameter of PH stainless steel. This Grey – fuzzy technique is one step ahead for turning on CNC. The objective of this study is to create a fuzzy model and optimize power consumption, surface roughness in turning of 15-5 PH using the improved grey-fuzzy algorithm and comparing the result of FIS with GRA.

2. Optimization

2.1 Grey Relational Analysis

Experimental results are integrated with grey relational approach to investigate the three input machining parameters (cutting velocity, feed rate and depth of cut) at three levels with respect to surface roughness and cutting force.

Step i: All the experimental observations are normalized in the range between zero (0) to one (1) which is known as data normaliztion.

Step ii: In this experimental study, lower the better criteria have been chosen for power consumption and Surface roughness.
Step iii: Grey Relational Coefficient (GRC) is calculated.
Step iv: The grey relational grade (Ѓi) is found using the following relation.

$$\Gamma_i = \frac{1}{n} \sum_{=1}^{Q} i(k) \qquad \ldots \quad (1)$$

Where, “Q” is the total number of response and “n” is the number of output responses. The parameter which has the higher value of grey relational grade is the optimal machining condition for the selected set of experiments.

2.2 *Fuzzy Inference Systems*

Fuzzy inference systems are multidisciplinary in nature and are associated with the process of formulating the mapping from input to output using fuzzy logic is termed as Fuzzy inference system. The formulated mapping provides a basis and helps in making decisions. The process fuzzy inference involves Membership Functions, Logical Operations and If-Then Rules. Mamdani-type and Sugeno-type are the two types of fuzzy inference systems implemented in the toolbox which vary accordingly by the way how outputs are determined. The application of Fuzzy inference systems (FIS) is successful in the fields of Automatic control, decision analysis, data classification, computer vision, and expert systems. Mamdani's fuzzy inference method was the first control systems built using fuzzy set theory and it is the most common fuzzy methodology seen.

2.3 *Grey-Fuzzy Analysis*

Designing a grey fuzzy technique involves the following steps:

- Plan the experiments accordingly with appropriate orthogonal array determining the level of machining parameters.
- Normalise the experimental results of power consumption and surface roughness according to the procedure of grey relational analysis.
- Calculate the grey relational coefficient and grey grade for the machining response.
- Establish the triangular membership function and fuzzy rule to fuzzify the grey relational coefficient of each response.
- Calculate the fuzzy multi-responses output by the max–min interface operation and transfer the output into a grey-fuzzy reasoning grade.
- Perform the response table and response graph to select the optimal level of machining parameters.
- Confirm the test and verifying the optimal setting of machining parameters.

3. Experimental Details

3.1 Materials and Processes

Turning experiments were conducted on LEADWELL CNC turning machine with a 7.5 kW motor, feed range up to 24000 mm/min and maximum spindle speed of 4500 rpm at dry condition. The experimental set-up used is shown in Figure. 1 and power consumption during machining was measured using Fluke Power quality analyser which was connected to the CNC turning machine. The material used for experiments was 15-5 PH stainless steel of 30 mm diameter and 120 mm length. Tool holder with a general specification PCLNL 1616 H12 and Tungsten carbide insert of CNMG 120408-GM coated with TiAlN was used as the cutting tool insert. Surface roughness (Ra) values were measured using Mitutoyo SJ 301 surface roughness tester with the assessment length and cut length of 4 mm and 0.8 mm were fixed respectively. Surface roughness was measured along the longitudinal direction of the machined surface at four different locations and the average values are evaluated for the responses.

Figure.1. Photograph of the power quality analyzer connected to the CNC machine

Table 1 Experimental plan and their response

Exp. No	Speed (V_c)	Feed (f)	Doc (a_p)	Power (P) Watts	Surface roughness ($R_{a)}$ µm
1	100	0.1	0.3	860	0.96
2	100	0.1	0.6	910	1.51
3	100	0.1	0.9	930	1.34
4	100	0.15	0.3	939	1.24
5	100	0.15	0.6	983	1.51
6	100	0.15	0.9	958	2.65
7	100	0.2	0.3	965	2.42
8	100	0.2	0.6	968	2.61
9	100	0.2	0.9	996	2.96
10	160	0.1	0.3	998	0.84
11	160	0.1	0.6	948	0.92
12	160	0.1	0.9	933	1.01
13	160	0.15	0.3	990	1.12
14	160	0.15	0.6	1020	1.15
15	160	0.15	0.9	1050	1.21
16	160	0.2	0.3	996	1.81
17	160	0.2	0.6	1030	1.96
18	160	0.2	0.9	1320	2.21
19	220	0.1	0.3	1020	0.51
20	220	0.1	0.6	1029	1.31
21	220	0.1	0.9	1045	1.18
22	220	0.15	0.3	1110	1.22
23	220	0.15	0.6	1119	1.37
24	220	0.15	0.9	1121	1.42
25	220	0.2	0.3	1120	1.91
26	220	0.2	0.6	1139	2.51
27	220	0.2	0.9	1180	2.65

To avoid uncertainty during dismantling and assembly of the workpiece, Surface roughness measurements were directly performed without disassembling the turned part from the CNC machine.

3.2 Plan of experiments

Based on the Taguchi's design of experiments (DOE) approach, the experiment was designed on a three level robust design with full factor replication. Cutting speed (Vc), Feed rate (f) and Depth of cut (ap) are considered as the input machining parameters, whereas power and surface roughness are the output parameters. The experimental plan and the observations of responses are shown in Table 1.

4. Results and Discussion

In this study, the effects of grey relational coefficient on grey fuzzy reasoning grade are presented. Table 2 shows the summary of GRG and their rank. From the Table 2 it is found that the 27th experiment is the optimal parameter for the multiple performance characteristics considered which the speed is 220m/min, feed is 0.2 mm/rev and depth of cut is 0.9. Table 3, shows the response table for means of grey relational grade and it is found that the major factor that affects the power and surface roughness is feed followed by depth of cut and the cutting speed. Figure 2 shows the main effect plots for the grey relational analysis. It is revealed that the GRG values are increased with an increase in feed and depth of cut.

Table 2 Summary of GRG, GFG and their Ranks

Exp. No	GRC		GRG	RANK	GFG	RANK
	P	Ra				
1	0.33	0.44	0.39	26	0.419	27
2	0.38	0.57	0.47	18	0.53	16
3	0.40	0.53	0.46	19	0.496	18
4	0.41	0.50	0.45	20	0.452	23
5	0.43	0.57	0.50	15	0.547	15
6	0.45	0.89	0.67	4	0.75	4
7	0.39	0.81	0.60	9	0.723	7
8	0.41	0.87	0.64	7	0.747	5
9	0.48	1.00	0.74	2	0.75	3
10	0.41	0.41	0.41	25	0.452	23
11	0.42	0.43	0.42	23	0.456	22
12	0.43	0.45	0.44	22	0.461	20
13	0.37	0.47	0.42	24	0.436	26
14	0.47	0.48	0.48	17	0.481	19
15	0.58	0.50	0.54	12	0.594	12
16	0.42	0.64	0.53	13	0.588	13
17	0.49	0.68	0.59	10	0.646	10
18	0.58	0.75	0.67	5	0.688	9
19	0.43	0.33	0.38	27	0.46	21
20	0.45	0.52	0.49	16	0.503	17
21	0.57	0.49	0.53	14	0.586	14
22	0.39	0.50	0.45	21	0.45	25
23	0.73	0.53	0.63	8	0.716	8
24	0.75	0.54	0.65	6	0.751	2
25	0.45	0.67	0.56	11	0.617	11
26	0.62	0.84	0.73	3	0.737	6
27	1.00	0.89	0.94	1	0.904	1

Table 3 Response table for grey relational analysis

Level	Average grey relational grade for each factor		
	A	B	C
1	0.5467	0.4433	0.4656
2	0.5000	0.5322	0.5500
3	**0.5956**	**0.6667**	**0.6267**
Delta	0.0956	0.2235	0.1611
Rank	3	1	2

Due to the increase in depth of cut the material removal rate is high and at deeper cuts the power required is higher comparatively to low depth of cut. When the level of speed increases from 100 to 220 m/min, the surface roughness is reduced. While the force induced during slow speed and high speed are considered, at high spindle speed, the force induced has been increased and produces less surface roughness than slow speed.

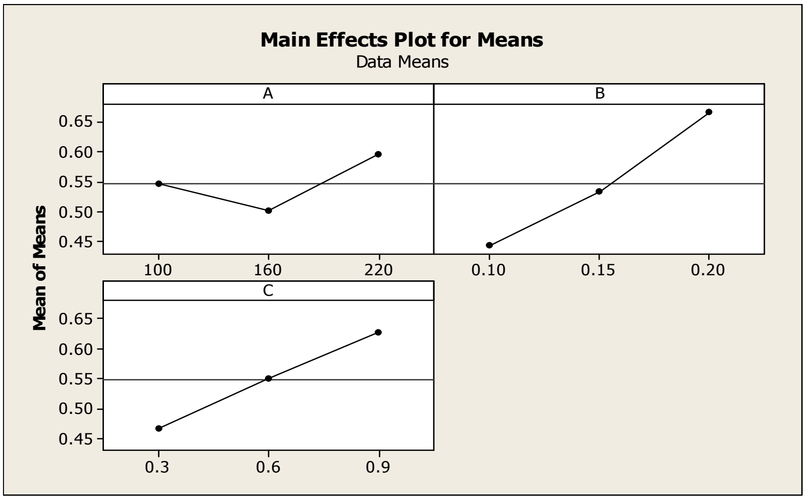

Figure 2 Main Effects Plots for GRG

Therefore speed at third level (220m/min), feed at third level (0.2mm/rev) and depth of cut at third level (0.9 mm) is the optimal parameter. Table 4 shows the range of fuzzy subsets which is used in fuzzy analysis. The values are categorised in to five subsets namely Very low, Low, Medium, High and Very High. Grey-fuzzy output was found using MATLAB. The optimal levels are obtained from the response table and response graph which are drawn from the average value of grey–fuzzy reasoning grade. Figure 3 shows the Triangular Membership function for GRC of power consumption and Surface roughness. The higher value of grey-fuzzy reasoning grade is selected as the optimal machining parameter.

Table 4 Range of fuzzy subsets

Condition	Range	Membership function
Very low (VL)	-0.25, 0,0.25	
Low (L)	0, 0.25, 0.5	
Medium (M)	0.25,0.5 ,0.75	Triangular
High (H)	0.5, 0.75, 1	
Very High (VH)	0.75, 1, 1.25	

Figure 4 shows the Triangular Membership function for Grey fuzzy grade. The fuzzy rules are formulated with the help of developed fuzzy model. Further the developed fuzzy model system is applied for prediction of grey fuzzy grade shown in Figure 5. The predicted values of GFG and their corresponding ranks are tabulated in the Table 5. From the Table it is observed that the ranks of GRG and GFG do not make more difference.

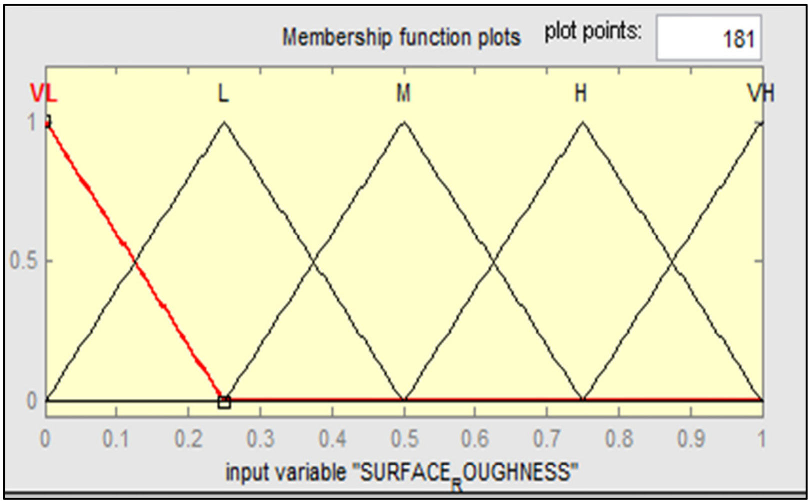

Figure 3 Membership function for GRC of Power Consumption and Surface Roughness

The values obtained from GRG and GFG are seemed to be in the same order. From the results of response table for grey fuzzy grade and Main Effects Plots for GFG which are shown in Table 5 and Figure 6 reveals that among the 27 experiments the optimal level setting of three machining parameters are speed at third level (220m/min) and feed at third level (0.2mm/rev) and depth of cut at third level (0.9 mm) is the optimal parameter.

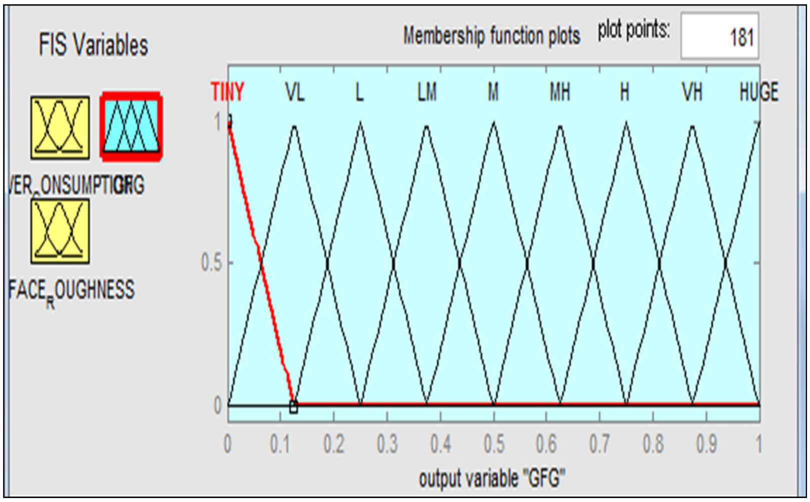

Figure 4 Triangular Membership function for Grey Fuzzy Grade

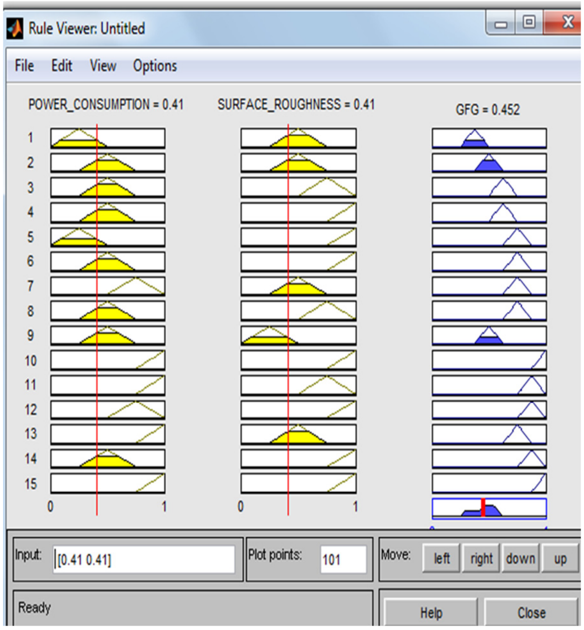

Figure 5 Fuzzy rule

Table 5. The response table for Grey Fuzzy Grade

Level	Average Grey Fuzzy Grade for each factor		
	A	B	C
1	0.6016	0.4848	0.5108
2	0.5336	0.5752	0.5959
3	**0.6360**	**0.7111**	**0.6644**
Delta	0.1024	0.2263	0.1537
Rank	3	1	2

The value of grey–fuzzy reasoning grade for each level is the larger the better in the response table. To verify the improvement of total performance characteristics, the confirmation test is conducted for the selected optimal level of the machining parameters. The comparison results of initial and optimal levels of machining parameters are listed in Table 6. The designate levels of individual optimal machining parameters are speed at first level (100 m/min) and feed at first level (0.1mm/rev) and depth of cut at first level (0.3 mm) for power consumption and for surface roughness speed at third level (220m/min) and feed at first level (0.1mm/rev) and depth of cut at first level (0.3 mm) is the optimal parameter. The result of the confirmation experiment is expressed by the estimated grey-fuzzy reasoning grade. Figure 7 shows the comparison between GRG and GFG and it implies that the grey fuzzy grade value is higher as compared to grey reasoning value. From the results of confirmation test, the multiple performance characteristics including power consumption and surface roughness have great improvement in machining by using the proposed approach in this study. As shown in Table 6, the results revealed that the power consumption increase from 860w to1180w and the surface roughness increases from 0.51μm to 2.65 μm and the estimated grey–fuzzy reasoning grade increases to 0.904. In this study the difference between initial and final is concerned with single and multi-response optimization. Initial optimization is followed by Taguchi method and the final followed by Grey-Fuzzy method. It is found that the desired performance characteristics in the turning process have great improvements through this grey fuzzy technique.

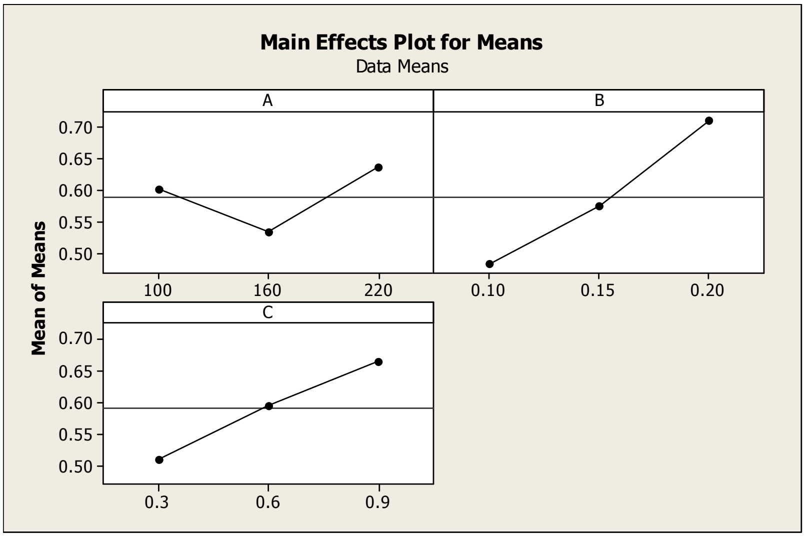

Figure 6 Main Effects Plots for GFG

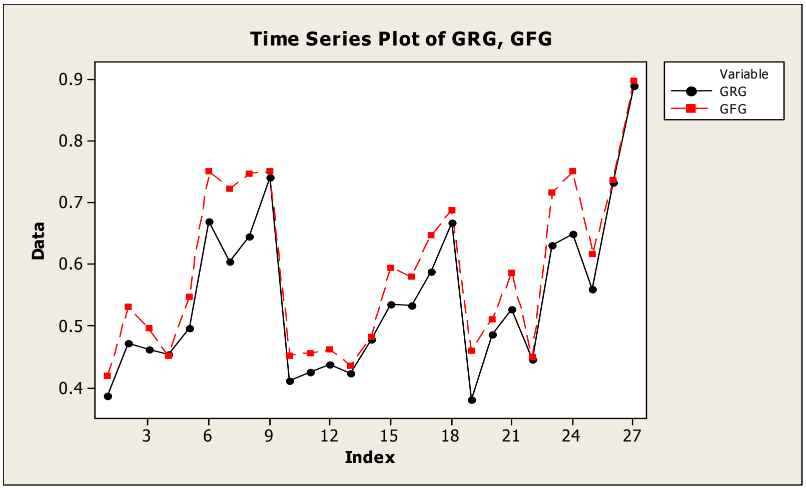

Figure 7 Comparison between GRG and GFG.

Table 6 Results of machining performance with initial and optimal setting of parameters

Designate Level	Power(W)	Surface Roughness (µm)	GFG
Initial	A1 B1 C1 860	A3 B1 C1 0.51	0.419
Predicted A3 B3 C3	986.56	1.571	0.590
Experimental A3 B3 C3	1180	2.65	0.904

5. Conclusions

- In this study, fuzzy model has been developed to optimize Power consumption and Surface Roughness in CNC machining process of PH stainless steel.
- The input parameters chosen are spindle speed, feed rate, depth of cut and the output responses considered are power consumption and surface roughness.
- While comparing the results of grey fuzzy-reasoning grade and grey relational grade, it is observed that there is an improvement in the values and thus the fuzziness is reduced.
- Using grey fuzzy technique the optimal parameter of input is speed 220 m/min, feed 0.2 mm/rev and depth of cut is 0.9mm.
- An increase in the value of predicted weighted GRG from 0.419 to 0.904 confirms the improvement in the turning operation using optimal values of process parameters.
- From the results of confirmation test, the multiple performance characteristics which include power consumption and surface roughness have great improvement by using this algorithm in this study.

References.

[1]. 15-5PH Stainless Steel, UNS S15500. AK Steel Corporation. 01 July 2005.

[2]. H.R. Habibi Bajguirani, Materials Science and Engineering A 338 (2002) 142–159.

[3]. Paulo Davim.J, “Machining: fundamentals and recent advances” Springer; 2008.

[4]. Ashok Kumar, Ybalaji, N Eswara Prasad,G Gouda And K Tamilmani, Sadhana_ Vol. 38, Part 1, February 2013, pp. 3–23._c Indian Academy of Sciences.

[5]. Ross, P. J. (1988). Taguchi techniques for quality engineering: loss function, orthogonal experiments, parameter and tolerance design.

[6]. Taguchi, G. (1986). Introduction to quality engineering: designing quality into products and processes.

[7].Lin, J. L., Wang, K. S., Yan, B. H., & Tarng, Y. S. (2000). 102(1), 48-55.

[8]. Elsayed, E. A., & Chen, A. (1993). The international journal of production research, 31(5), 1117-1132.

[9]. Camposeco-Negrete, C. (2013). Journal of Cleaner Production, 53, 195 203.

[10]. Sahoo, A. K., & Pradhan, S. (2013). Measurement, 46(9), 3064-3072.

[11]. Rajmohan. T, K. Palanikumar, S. Prakash,Composites: Part B 50 (2013) 297–308.

[12]. Hanafi, I., Khamlichi, A., Cabrera, F. M., Nuñez Lopez, P. J., & Jabbouri, A. (2012). Measurement, 45(6), 1424-1435.

[13]. Pattnaik, S., Karunakar, D. B., & Jha, P. K. (2013). The International Journal of Advanced Manufacturing Technology, 67(5-8), 1577- 1587.

[14]. Gupta, A., Singh, H., & Aggarwal, A. (2011). 38(6), 6822-6828.

[15]. Gopalsamy, B. M., Mondal, B., & Ghosh, S. (2009). The International Journal of Advanced Manufacturing Technology, 45(11-12), 1068-1086.

[16]. Torlak, G., Sevkli, M., Sanal, M., & Zaim, S. (2011). Expert Systems with Applications, 38(4), 3396-3406.

[17]. Asokan, P., Kumar, R. R., Jeyapaul, R., & Santhi, M. (2008).The International Journal of Advanced Manufacturing Technology, 39(1-2), 55-63.

[18]. Hanafi, I., Khamlichi, A., Cabrera, F. M., Almansa, E., & Jabbouri, A. (2012). Journal of Cleaner Production, 33, 1-9.

[19]. Parida, B., & Pal, S. (2015). Science and Technology of Welding and Joining, 20 (1), 35-41.