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Research paper

Multi-Objective Optimization and Modeling of Surface Roughness in Inconel 718 using Taguchi Grey Relational Analysis and Response Surface Methodology

[1]Abhijith S, [2]Srinivasa Pai P, [3]Bhaskara Achar, [4]Grynal D'mello

Department of Mechanical Engineering, NMAM Institute of Technology, Nitte574110, India
**Corresponding author Email: [1]abhijith581@gmail.com , [2]srinivasapai@nitte.edu.in , [3]bhaskarap@nitte.edu.in , [4]grynal@nitte.edu.in*

Abstract

Nickel-based super-alloys have been widely used in aircraft, nuclear industry, transfer rolls, single crystal turbine blades, heat treating trays, and die blocks due to their thermal resistance and their ability to retain mechanical characteristics at high temperatures. In this work, dry turning experiments on Inconel 718 have been performed using uncoated carbide inserts at various cutting speeds, feeds and a constant depth of cut. Taguchi based Grey Relational Analysis (GRA) optimisation has been used to optimise the surface roughness parameters namely Ra and Rt. Taguchi GRA has established optimal machining conditions for machining Inconel 718 considering cutting tool vibrations, temperature and tool wear as input parameters. The optimised machining conditions are 80m/min cutting speed and 0.1mm/rev feed rate, and considering other parameters, it is 9 g for cutting vibration, 95ºC for temperature and 0.08mm for tool wear. Analysis of Variance (ANOVA) showed that feed rate (70.35%) is the most significant factor influencing surface roughness parameters followed by cutting speed (16.12%), tool wear (9.8%), vibrations (3.4%) and temperature (0.4%). Response Surface Methodology has been used to develop multiple regression models to predict surface roughness. The quadratic model developed has a R2 value of 0.917 and results in a prediction accuracy of 75% for Ra and R2 value of 0.906 with prediction accuracy of 75% for Rt.

Keywords: *Surface roughness, Cutting speed, feed , RSM, GRA*

1. Introduction

Nickel based alloys such as Inconel 718 has application in aero engine parts, rotor blades, engine parts etc. and is classified as difficult to cut materials [1]. Surface finish is a primary requirement for designing mechanical parts and it indicates quality of manufacturing processes. In machining process of Inconel 718, the surface roughness is mainly affected by rate of feed, cutting edge angle, nose radius and plan approach angle [2]. The poor thermal conductivity of Inconel 718 leads to high temperatures in the cutting zone

resulting in heat dissipation during machining process [3]. The unavoidable dynamic interactions between the cutting tool and work material cause vibrations and hence chatter. This chatter has adverse effect on various parameters like surface roughness, dimensional accuracy, tool wear etc.[4]. R Thirumalai et al (2012) conducted study on surface roughness and flank wear in turning of Inconel 718. Feed rate had significant effect on surface roughness, whereas the cutting speed had a medium effect. Depth of cut had no significance [5]. RSM is a useful mathematical and statistical technique for modelling of problems in which dependent parameters are affected by several independent parameters. A number of researchers have applied RSM for modelling and analysis of process parameters in machining [6]. Grynal D'Mello et al (2013) investigated the influence of cutting parameters on two surface roughness parameters i.e R_a and R_t , during high speed turning of Ti-6Al-4V.The surface roughness modelling was done using RSM. The experimental studies showed that surface roughness parameters R_a and R_t increases with increase in feed rate and cutting tool vibrations, while increase in cutting speed and tool wear decreased the surface roughness [7]. Grey system theory gives a proficient control on the uncertainty, various inputs parameters and incomplete data. The main limitation of the Taguchi S/N ratio method is that it can only be applied to solve single-output optimization problems.

To optimize multiple responses, Taguchi design with GRA is employed to choose the optimum conditions for machining process [8]. N Manikandan et al (2014) performed multiple outputs optimization in electrochemical drilling of Inconel 625 using Taguchi based GRA. Feed rate was the significant variable for the desired output characteristics. The optimal solution for the outputs are feed rate at 0.20 mm/min, electrolyte concentration at 25% and flow rate at 0.60 lit/min [9]. In this study, the turning process was conducted using uncoated carbide inserts by varying the cutting speed, feed rate and having a constant depth of cut. The effects of temperature, vibration and tool wear were also analysed. These parameters are generally considered as outputs of a machining process. This study is different in this regard, where these parameters are being used as inputs. This study aims to perform multi objective optimisation using GRA and RSM for modelling surface roughness obtained in turning Inconel 718 in terms of R_a and R_t .The goal is to achieve optimisation and modelling results for making significant conclusions regarding surface roughness.

2. Materials and Method

A cylindrical Inconel 718 bar of 50mm diameter and 200 mm length was used as work piece in a dry turning process. Uncoated carbide inserts 883 with MR4 chip breaker (SECO make) which is flat faced; rhomboidal in shape has been used. The tool holder considered for machining is PCLNL 2020K12JETL (SECO MAKE) for holding the inserts during experiments. The turning experiments were conducted on a CNC turning centre, HMT Stallion100SU. Experiments have been carried out in dry condition. The experimental setup is shown in Fig 1. The output parameters evaluated were surface roughness, temperature, tool wear and vibrations. Totally 9 cutting experiments were conducted, considering 3 cutting speeds and feeds, keeping depth of cut constant. Experimental conditions are given in Table1

Table 1: Experimental conditions

Parameters	Experimental Conditions		
Cutting speed,(m/min)	40	60	80
Feed rate (mm/rev)	0.1	0.15	0.2
Depth of cut (mm)	0.5 (Constant)		

Fig 1: Experimental Setup

Fig 2: Surface Roughness measurement system

The tool wear is measured in terms of maximum flank wear (VB_{max}) Measurement of flank wear was carried out after each machining pass using a Mitutoyo Tool Maker's Microscope (TM 505/510) with a magnification of 15 X. Experiments were continued till the flank wear reached 0.4mm as per ISO 3685[10] .The cutting tool vibrations were measured using a Model 65-10 Isotron ® triaxial accelerometer (Meggit make) online. The accelerometer was mounted on the tool holder near the cutting zone during machining. The accelerometer sensed the vibration signals in x, y and z directions i.e depth of cut, speed and feed directions respectively. Surface roughness is measured using stylus type instrument (Taylor and Hobson, Talysurf) offline. Surface roughness parameters considered were R_a and R_t. The surface roughness measurement system is shown in Fig 2. The temperature at tool tip–work piece interface was measured using 30" Dual Laser Infrared Ray Thermometer measuring device, which was firmly focused at the tooltip and work piece interface. On an average four readings were taken in a machining pass and its mean value is calculated.

3. Multi Objective Optimization Using Grey Relational Approach

3.1 Introduction

The Grey system primarily deals with the relational analysis and model construction of a system in relation to the uncertainty and completeness of a problem. To understand a problem, the methods of prediction and decision making is used [11]. To solve Multi objective optimization problems by GRA, the multi-outputs problem is converted to a single-objective problem, and then the efficient quality characteristics corresponding to the optimum level of cutting parameters are obtained [12]. Table 2 shows the sample experimental data (both inputs and output).

3.2 Grey Relational Analysis

The analysis of the process has been conducted in the following stages [13]:

Step 1: Normalization of Data
The initial step is normalization of the data in the range between 0 and 1. In this investigation "smaller the- better" condition is adopted for normalization of all the outputs as in eqn (1)

$$x_i^*(k) = \frac{(\max x_i^{(o)}(k) - x_i^{(o)}(k))}{(\max x_i^{(o)}(k) - \min x_i^{(o)}(k))} \;..... \qquad (1)$$

Step 2: Estimating deviation sequence
The deviation sequence Δ0i (k) is the difference between comparability sequence xi*(k) after normalization stage and reference sequence xo*(k). It is given by eqn (2) as:

$$\Delta 0_i\,(k) = |x_i^*(k) - x_0^*(k)| \;....... \qquad (2)$$

Step 3: Calculation of Grey Relational Coefficients (GRC)
It gives the relationship between the best and actual normalized data value. The grey relational coefficient is equal to 1 if the two outputs hold good at all points. The grey relational coefficient γ (x_o (k), x_i (k)) is given by eqn (3)

$$\gamma(x_o(k), x_i(k)) = \frac{(\Delta_{\min} + \zeta\Delta_{\max})}{(\Delta_{oi}(k) + \zeta\Delta_{\max})} \;... \qquad (3)$$

where Δ_{min} is the smallest value of $\Delta 0_i$ (k) = $\min_i \min_k | x_o^*(k) - x_i^*(k)|$ and Δ_{max} is the largest value of $\Delta 0_i$ (k) = $\max_i \max_k | x_o^*(k) - x_i^*(k)|$, x_o^* (k) is ideal normalised data, x_i^* (k) is the normalised comparability sequence and ζ is the differential coefficient. The value of ζ can be controlled with the actual need and it is in the range between 0 and 1, here it is taken as 0.5.
Step 4: Determination of Grey Relational Grade -
The overall estimation of the multiple outputs is based on the Grey Relational Grade (GRG). The GRG is an average of the grey relational coefficients which is given as follows:

$$\gamma\,(x_o, x_i) = 1/m \sum_{i=1}^{m} \gamma(x_o(k), x_i(k)) \;..... \qquad (4)$$

Step 5: Obtaining optimal parameters and significant input conditions
The GRG determined for each sequence is taken as output for further estimation. The larger the better condition is applicable for estimating the GRG. Hence, a larger value shows the efficient

results of the process. The GRA has been carried out using Minitab 17.0 [14]. The rank wise influence of input parameters is also obtained.

3.3 Analysis of Variance (ANOVA)

ANOVA is a computational technique which efficiently estimates the contributions of each process parameter variation to the overall response variation. The Statistical software Minitab 17.0 has been utilized to determine the significant cutting parameters, affecting the multiple performance characteristics. The application of ANOVA technique makes it less cumbersome to analyse the results and hence, makes it fast to arrive at the conclusions [15].

4. Modelling: Response Surface Methodology

RSM is a combination of mathematical theory and statistical process, which is applicable for modelling and analysing problems in which an output is dependent on different input parameters and the aim is to optimize this output. In this work, RSM has been used for modelling and analysing the surface roughness parameters in terms of cutting parameters and other output parameters [16]. The mathematical relationship between input variables and output variables can be determined in terms of a first order model as represented in eqn(5)

$$y = \beta_o + \beta_1 x_1 + \beta_2 x_2 + ...\beta_k x_k + \varepsilon \;....... \qquad (5)$$

where, y is the predicted value, $x_1,x_2.....x_k$ are the input variables that influences the output variable, y, β_o is the intercept,€ represents the error observed in the response. The second order model is given in eqn (6)

$$y = \beta_o + \sum_{i=1}^{k} \beta_i x_i + \beta_{ii} x_i^2 + \sum_{i<j}\sum \beta_{ij} x_i x_j + \varepsilon \;..... \qquad (6)$$

where, x_i represents the variables that correspond to the studied machining parameters[7].The contributions and effect of cutting speed, feed rate, tool wear, cutting tool vibrations and temperature on R_a(µm) and R_t (µm) are studied. To further understand the effect of the interactions of the various input parameters, second order polynomial models have been developed. The regression analysis has been performed using Minitab17.

5. Result & Discussions

5.1 Determination of Optimal Machining Parameters

Table 2 shows the sample input data namely cutting speed (m/min), feed (mm/tooth), cutting tool vibrations, tool wear and temperature and responses namely R_a (µm) and R_t (µm). In the application of GRA, the data processing is done as follows: Initially, the normalisation is done in the range 0 to 1 and is shown in Table 3. Smaller the better condition is employed for normalisation of all the outputs using eqn (1).The second step is to determine a deviation sequence which is the difference between the comparability sequence x_i*(k) and reference sequence x_o*(k) after normalization, which is determined using eqn (2).
After determining the deviation sequence, the third stage is to determine GRC's for every experimental data which are found using eqn (3). The GRC values are given in Table 3. The fourth stage is to obtain GRG which are obtained by the average of GRC's as shown in Table 3. The larger the better condition is used for analysing the GRG. Since larger value indicates the efficient performance of the experiments, the higher value of GRG indicates best machining conditions [13]. The corresponding ranks based on GRG are given in table 3. Fig 3 shows the optimal process conditions for machining Inconel 718. From Table 3, the highest GRG value is obtained for 43rd experiment, which indicates that optimised conditions for turning of Inconel 718 are 80 m/min cutting speed,0.1mm/rev of feed rate , 9 g value of cutting tool vibrations, 95ºC temperature and 0.08mm of tool wear. Fig 3 shows the main effect plots of individual input parameters based on mean of GRG's. The larger value of GRG indicates the optimised parameters. Table 4 shows the response table for means based on GRG at each level, where delta is the difference between the largest value and lowest value for different level of parameters. The larger delta value indicates, the most significant factor. Hence the most influential parameter in turning of Inconel 718 is feed rate followed by cutting speed, tool wear, vibrations and temperature.

30	0.5431	0.6061	0.5746	34
32	0.7655	0.6551	0.7103	6
33	0.5789	0.6725	0.6257	25
34	0.6544	0.6248	0.6396	24
35	0.379	0.3933	0.38615	54
36	0.4616	0.5089	0.48525	44
37	0.402	0.5125	0.45725	48
38	0.4333	0.4279	0.4306	50
39	0.481	0.5731	0.52705	40
40	0.4055	0.5636	0.48455	45
41	0.4776	0.5185	0.49805	42
42	0.5574	0.6056	0.5815	32
43	0.4948	0.8209	0.8468	1
44	0.9596	0.6765	0.60625	28
45	0.8803	0.6707	0.73535	4
46	0.7094	0.7613	0.81805	2
47	1	0.6936	0.65785	20
48	0.5724	0.6401	0.7755	3
49	0.5575	0.6248	0.7206	5
50	0.6962	0.6772	0.6867	14
51	0.6013	0.5565	0.5789	33
52	0.6257	0.7103	0.668	16
53	0.7304	0.4917	0.61105	26
54	0.5125	0.4897	0.5011	41

5.2 ANOVA Results

The outcome of ANOVA are shown in Table 5. From Table 5, it is clear that the feed rate (70%) influences most on surface roughness parameters and it is followed by cutting speed (16%), tool wear (9.8%), vibrations (3.4%) and temperature (0.4%).

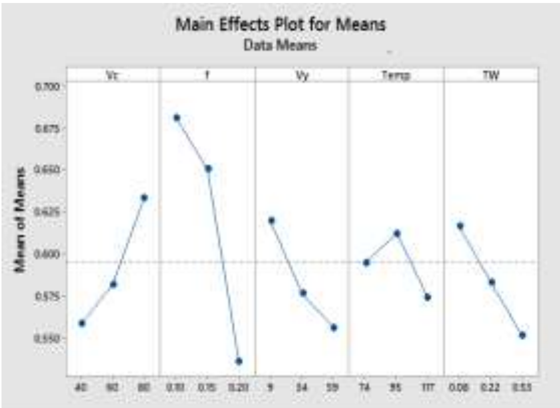

Fig 3: Main effect plots for Means of GRG

Table 4: Response Table for Means based on GR**G**

Level	Vc	f	Vy	Temp	TW
1	0.5582	0.6812	0.6198	0.5947	0.6165
2	0.582	0.6506	0.5765	0.6121	0.5833
3	0.6336	0.5362	0.5561	0.5742	0.5511
Delta	0.0754	0.145	0.0637	0.0378	0.0653
Rank	2	1	4	5	3

Table 5: Analysis of Variance

Source	DF	Adj SS	Adj MS	F-Value	P-Value	% C
Vc	2	0.04496	0.04496	6.54	0.009*	16.12
f	2	0.19616	0.19616	28.54	0*	70.35
Vy	2	0.00113	0.00113	1.37	0.031*	3.4
Temp	*2*	*0.00386*	*0.00386*	*0.16*	*0.457*	*0.4*
TW	*2*	*0.00063*	*0.00063*	*3.96*	*0.014**	*9.8*
Residual Error	*48*	*0.32993*	*0.00687*			
Total	*58*	*0.64342*				

5.3 Confirmation Experiments

After obtaining the optimal level of input parameters, the next step is to predict and analyse the efficiency of the performance characteristics, using the optimal level of the machining conditions. The estimated GRG, γ using the optimum level of the machining conditions can be calculated using eqn (7).

$$\gamma = \gamma_m + \sum_{i=1}^{q} (\gamma_j - \gamma_m) \quad \cdots\cdots\cdots\cdots\cdots \qquad (7)$$

where γ_m is the total mean of the GRG, γ_j is the mean of the GRG at the optimum level and *q* is the number of machining conditions, that significantly influence the multiple performance characteristics [8]. Based on eqn (4), the estimated GRG using the optimal machining conditions can be obtained. N Manikandan et al (2017) also performed multiple output optimisation in drilling of Inconel 625 using Taguchi based GRA and they obtained an improvement of 0.4580 in the grey relational grade by confirmation experiment [9]. Table 6 shows the result of the confirmation experiment using the optimal machining parameters. It is seen that the surface roughness parameter (R_a) is improved from 0.2497 to 0.2477 µm and the R_t is improved from 1.8265 to 1.6897 µm. There is an improvement of 0.2015 in the GRG.

5.4 Rsm Modelling

5.4.1 RSM Model Development for Ra and RT

In order to evaluate the results of turning process, the experimental dataset were used to develop models using RSM. Out of 54 experimental data set, 46 data were considered to be training data and 8 dataset as test data. The quadratic model developed using the input and output parameters
are represented as:

R_a = -3.14+ 0.0410V_c+ 25.60 f- 0.0144 V_y+ 0.0148 T-1.90TW-0.000305 $(V_c)^2$-49.8$(f)^2$- 0.000215 $(V_y)^2$-0.000072$(T)^2$+ 1.32 $(TW)^2$+ 0.0108 (V_c X f)- 0.000080 (V_c X V_y) - 0.000082 (V_c X T) + 0.0150 (V_c X TW) + 0.0457 (f X V_y) - 0.0442 (f X T) - 17.3 (f X TW)+ 0.000259 (V_y X T)+ 0.0069 (V_y X TW)+ 0.0263(T X TW)

Similarly, the quadratic model developed for R_t is represented as:

R_t = -12.51+0.170V_c + 54.5f - 0.013V_y + 0.164T- 17.2 TW+ 0.00032 $(V_c)^2$ -191$(f)^2$+ 0.00142 $(V_y)^2$ - 0.00139$(T)^2$+ 31.7$(TW)^2$- 0.888 (V_c X f)+ 0.00220 (V_c X V_y)-0.000145 (V_c X T)+ 0.015 (V_c X TW)- 0.452 (f X V_y)+ 1.01(f X T)- 32(f X TW)- 0.00021(V_y X T)-0.446 (V_y X TW)+ 0.128(T X TW)

Table 6: Results of machining process using initial and optimal machining parameters

	Initial Machining Parameters	**Optimal Machining Parameters**	
		Prediction	**Experiment**
Setting Level	A1B1C1D1E1	A3B1C1D2E1	A3B1C1D2E1
R_a	0.2497		0.2477
R_t	1.8265		1.6897
Grey Relational Grade	0.6453	0.8236	0.8468
Improvement in GRG	0.2015		

5.4.2 RSM Results

For test dataset, the quadratic models developed had R^2 of 0.917 for R_a and prediction accuracy obtained is 75%. Similarly for R_t the R^2 value obtained is 0.906 and prediction accuracy is 75%. ANOVA is used to evaluate the experimental data and identify the factors which have a significant influence on the output variables i.e. surface roughness parameters R_a and R_t. This analysis has been performed for 95% confidence level. The p value less than 0.05 indicates that the surface roughness model is significant. Lower p values show that the factor has higher probability of falling within the ranges, which impact the output of the experiment [7]. Table 7 shows the ANOVA results for R_a, where the most significant factor is feed rate followed by cutting speed, tool wear, vibrations and temperature. Table 8 shows the ANOVA results for R_t, which also indicates that temperature is the least significant factor and feed rate followed by cutting speed, tool wear and vibrations are significant factors. To further understand the effect of interactions, second order polynomial models have been developed. The ANOVA results given in Table 7 shows that square terms involving cutting speed and feed are significant .Interaction terms between cutting speed and feed, feed and cutting tool vibrations, feed and temperature, feed and tool wear were found to be significant, the other interactions have no significance Similarly from Table 8, it is found that square terms related to feed rate are significant. The interaction terms between cutting speed and feed, feed and tool wear is significant. Where as the other interactions have no significance. Fig 4 and Fig 5 shows the plot of predicted and experimental values considering test data for R_a and R_t respectively. The figures show closeness between the two values, but the closeness is more significant for R_a than R_t.

Table7: ANOVA Analysis by RSM for Ra

Analysis of Variance

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Model	20	3.26413	0.163206	18.45	0
Linear	5	0.50505	0.101011	11.42	0
Vc	1	0.01124	0.01124	0.20	0.000
f	1	0.01471	0.014712	1.66	0
Vy	1	0.00003	0.000026	0	0.041
T	1	0.01486	0.014865	1.68	0.006
TW	1	0.0003	0.000303	0.03	0.020
Square	5	0.14365	0.028729	3.25	0.021
Vc*Vc	1	0.01475	0.014748	1.67	0.049
f*f	1	0.04717	0.047174	5.33	0.029
Vy*Vy	1	0.01463	0.014632	1.65	0.21
T*T	1	0.00388	0.003885	0.42	0.729
TW*TW	1	0.00455	0.004549	0.51	0.066
2-Way	10	0.1703	0.01703	1.93	0.000
Vc*f	1	0.00031	0.000308	0.03	0.012
Vc*Vy	1	0.00117	0.001168	0.13	0.069
Vc*T	1	0.00068	0.000677	0.08	0.351
Vc*TW	1	0.00539	0.005388	0.61	0.057
f*Vy	1	0.00289	0.002887	0.33	0.037
f*T	1	0.0018	0.001799	0.2	0.035
f*TW	1	0.01957	0.019572	2.21	0.045
Vy*T	1	0.00646	0.006463	0.73	0.401
Vy*TW	1	0.00113	0.001132	0.13	0.097
T*TW	1	0.00469	0.004693	0.53	0.473
Error	25	0.22116	0.008846		
Total	45	3.48529			

Table8: ANOVA Analysis by RSM for Rt

Analysis of Variance

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Model	20	64.089	3.20445	3.69	0.001
Linear	5	3.1037	0.62075	0.71	0.619
Vc	1	0.076	0.07597	0.09	0.009
f	1	0.2714	0.27137	0.31	0.002
Vy	1	0.0248	0.02483	0.03	0.045
T	1	0.0104	0.01042	0.01	0.365
TW	1	2.224	2.224	2.56	0.015
Square	5	4.1791	0.83582	0.96	0.46
Vc*Vc	1	0.0135	0.0135	0.02	0.050
f*f	1	0.5982	0.59821	0.69	0.046
Vy*Vy	1	0.8185	0.81851	0.94	0.341
T*T	1	0.4611	0.46108	0.53	0.473
TW*TW	1	1.8719	1.87187	2.15	0.062
2-Way	10	2.7023	0.27023	0.31	0.971
Vc*f	1	0.9935	0.99349	1.14	0.042
Vc*Vy	1	0.3797	0.37973	0.44	0.009
Vc*T	1	0.1828	0.18281	0.21	0.65
Vc*TW	1	0.0049	0.00491	0.01	0.925
f*Vy	1	0.184	0.18402	0.21	0.075
f*T	1	0.7011	0.70108	0.81	0.378
f*TW	1	0.0587	0.05873	0.07	0.012
Vy*T	1	0.0044	0.00442	0.01	0.944
Vy*TW	1	1.5425	1.54248	1.77	0.062
T*TW	1	0.1284	0.12837	0.15	0.706
Error	25	21.7273	0.86909		
Total	45	85.8164			

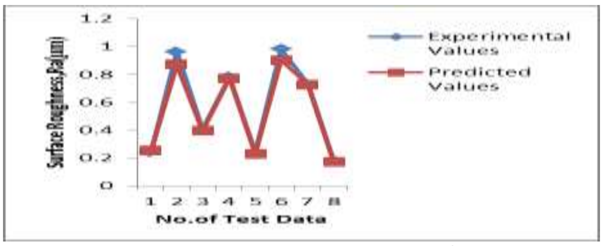

Fig 4: Predicted and Experimental values obtained for Ra (test data)

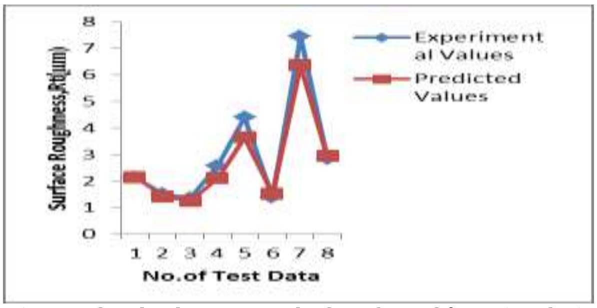

Fig 5: Predicted and Experimental values obtained for Rt (test data)

6. Conclusion

Key findings of the multiple objective optimisation using GRA techniques and RSM modelling studies are as follows:

1. From Taguchi based GRA approach, it is found that the optimal machining conditions for turning of Inconel 718 are 80 m/min cutting speed, 0.1 mm of feed rate .Further the other parameters which are generally considered as outputs in a machining process are considered as inputs in this work and are found to have an influence on surface roughness with the following values: 9g for cutting tool vibrations, 95ºC for temperature and 0.08mm for tool wear.
2. ANOVA showed that the feed rate (71%) is the most significant factor influencing surface roughness parameters and it is followed by cutting speed (16%), tool wear (10%), vibrations (3.5%) and temperature (0.4%).
3. From confirmation test, using the optimal machining parameters, it is seen that the surface roughness parameter (R_a) is improved from 0.2497 to 0.2477 µm and R_t is improved from 1.8265 to 1.6897 µm.
4. From RSM analysis for test dataset, the quadratic models developed had R^2 of 0.917 for R_a and prediction accuracy obtained is 75%. Similarly for R_t the R^2 value obtained is 0.906 and prediction accuracy is 75%, which is a reasonably good modelling performance.

Thus GRA can be effectively used for multi objective optimisation and RSM can be used for effectively modelling of surface roughness in turning of Inconel 718 using uncoated carbide inserts.

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