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Optimizing Inconel 825 machinability: A comprehensive approaches using Taguchi design, Grey-Fuzzy, and principal component analysis

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Abstract

Nickel super alloys have remarkable thermo mechanical capabilities, making them important in industries such as nuclear, chemical, petrochemical, and aerospace. Conversely its difficult machining and cause the poor surface finish and tool wear and so on. This study proposes optimizing machining parameters of Inconel 825 such as cutting speed, feed, and depth of cut towards the responses such as surface roughness, tool flank wear, and cutting force. Optimization of process parameter for this study; the Taguchi Design of Experiments, Grey Relational Analysis, Fuzzy Logic, and Principal Component Analysis (PCA) were used. Experimental were conducted using an L9 orthogonal array and outcomes were evaluated using ANOVA towards the most influencing process parameter. Form the results indicated that the cutting is the most influencing compare with the other parameters. The optimal parameters for turning Inconel 825 were found to be 50 m/min cutting speed, 0.2 mm/rev feed rate, and 0.6 mm depth of cut towards the machining responses. This results conduits towards the machining efficiency of Inconel 825 for industrial applications.

1. Introduction

Nickel based super alloy were most essential materials in contemporary industrial owing to their superior mechanical properties and corrosion resistance at higher temperature [1]. Due to this properties and it is most suitable for many application such as aerospace, petrochemical, nuclear power and chemical industries[2]. Amongst these Inconel 825 has exceptional properties such as corrosion resistance and thermal stability [3]. It contains nickel, chromium, iron, molybdenum, copper and titanium enhancing the resistance to oxidation. However, while machining of Inconel 825 is difficult in challenges in industrial environments [4]. Due to deprived machinability and often outcomes in higher cutting force, irregular surface and tool wear happen. While Inconel 825 is extoled for its routine in difficult operating environments; which remain a challenging such as higher work hardening rate, lower thermal conductivity, poor chip control and wear [5]. Hence optimization is required for better surface roughness, minimum tool degradation and reduction in operational cost [6]. These problems combines reduce the production rate but increase the manufacturing cost. Consequently, an optimization of machining parameters is most significant towards improve the machinability, reduction in surface defects and better tool life [7] . Thakur et al. examined tool wear in Inconel 825 turning and discovered that flank wear increases with greater

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cutting speeds and also studied on Inconel 718 and found that coated tools performs with respect to the cutting and fee force [8] .

Senthilkumaar et al investigated surface roughness in relation to feed rate and discovered that larger feed rates, as well as lower speeds and deeper cuts, resulted in a higher material removal rate and surface polish [9]. Rajyalakshmi and Ramaiah studied the combination of Grey Relational Analysis (GRA) and Taguchi for WEDM optimization of Inconel 825, which shows that the improvement has been observed in machining [10]. Even though, the fuzzy logic results were autonomously and latest studies improvements of GRA in ambiguous machining conditions [11] . To overcome this principal compound analysis is the better choice towards the variable influencing machining responses [12] . Asiltürk and Akkus reported that the better outcome such as surface roughness and material removal rate in turning. In Inconel 738 and Inconel 718, PCA optimization were used for better performance in machining but these not scientifically used to Inconel 825 [13]. Lila Imani et al. examined both the Artificial Neural Networks (ANN) and Genetic Algorithms (GA) in Inconel 738; the outcome inveterate the ANN but the impediment in ANN and also deficiency in physical interpretability [14]. The traditional methods such as response surface methodology, GA and ANN were used in optimization towards turning. But these techniques require maximum experimentation and also need huge data. Taguchi combined with multi objective optimization had accepted owing to the accuracy and woks in limited experimental data's and produce better results [15].

Novelty of this research work was cohesive use of Taguchi Design of Experiments, Grey Fussy and PCA for optimization of machining parameters of Inconel 825 with limited earlier study in this background. Whereas the previous studies reported that single approaches, in this work distinctively combines these three approaches for multi response optimization. This cohesive approach enhances the prediction correctness for machining performances in respect with the machining parameters such as cutting speed, feed rate and depth of cut. These novel and effective findings improve the machinability of Inconel 825 while also facilitating the way for further materials.

2. Materials and Methods

Inconel 825, a nickel-based super alloy and widely employed in a range of industries such as aerospace and automobile, etc., This study focuses on turning of Inconel 825 and optimization techniques were employed. Machined components will has 3mm layer of the outer surface been pre-machined to ensure excellent machining quality. The raw material consisted of bars 30 mm in diameter and 80 mm in length. It has largely composed of nickel, iron, and chromium. Fig. 1, shows the machined Inconel 825.

Fig. 1. Inconel 825

Based on previous research, three cutting parameters such as cutting speed, feed rate, and depth of cut were selected for this experimental work [4, 16, 17]. The CNC Super Jobber 500 LM machine, which has a 10 KW motor drive and an operating range of 30 to 300 rpm, was chosen due to its low. The trials were planned using Taguchi's relational analysis. An L9 orthogonal array with 3 variables at three levels was used for optimization results. MINITAB 16 software was used for the Design of

Experiments, which generated the L9 orthogonal array and provided a wide range of potential cutting settings [18]. Table 1 presents the cutting parameter and their range.

Table 1. Input process parameters and level

Parameter	Unit	Level		
		1	2	3
Cutting Speed	m/min	50	70	90
Depth of cut	mm	0.2	0.4	0.6
Feed rate	mm/rev	0.1	0.2	0.3

3. Results and Discussions

3.1 Taguchi Analysis

Table 2 denotes the Taguchi L9 orthogonal array; the three-input parameter used in this study as cutting speed, feed rate and depth of cut and their three different level. The identifications of individual and interaction of the input parameter; which succeeding analysis of surface roughness, cutting force and flank wear in machining i.e., turning of Inconel 825.

Table 2. Design of experiments (DoE) – L9 results

Run Order	Cutting Speed	Depth of Cut	Feed Rate	Surface Roughness (μm)	Cutting Force (N)	Flank wear (μm)	S-N Ratio	Std. Dev.	Mean
1	50	0.2	0.1	2.54	428.36	152.63	-3.21	215.98	194.51
2	50	0.4	0.2	4.15	449.54	172.65	-2.77	224.88	208.78
3	50	0.6	0.3	3.75	444.25	176.28	-2.63	221.97	208.09
4	70	0.2	0.2	4.23	461.62	189.69	-2.45	230.05	218.51
5	70	0.4	0.3	4.05	463.52	191.25	-2.44	231.04	219.61
6	70	0.6	0.1	3.15	470.67	196.25	-2.44	234.94	223.36
7	90	0.2	0.3	4.94	490.57	220.39	-2.02	243.33	238.63
8	90	0.4	0.1	3.59	486.54	215.36	-2.14	242.08	235.16
9	90	0.6	0.2	4.48	475.67	203.57	-2.25	236.54	227.91

Table 3. Analysis of variance (ANOVA)

Source	DF	Contribution	Seq SS	Adj SS	Adj MS	F	P
S-N Ratio							
Cutting Speed	2	79.41%	0.80834	0.80834	0.40417	7.91	0.011
Depth of Cut	2	2.49%	0.02534	0.02534	0.01267	0.25	0.080
Feed Rate	2	8.06%	0.08204	0.08204	0.04102	0.80	0.055
Residual Error	2	10.04%	0.10223	0.10223	0.05111		
Total	8	100.00%	1.01795				
Means							
Cutting Speed	2	87.09%	1365.03	1365.03	682.51	9.47	0.009
Depth of Cut	2	1.55%	24.26	24.26	12.13	0.17	0.085
Feed Rate	2	2.17%	33.96	33.96	16.98	0.24	0.080
Residual Error	2	9.20%	144.14	144.14	72.07		
Total	8	100.00%	1567.39				
Std. Dev.							
Cutting Speed	2	87.89%	585.513	585.513	292.757	9.14	0.009
Depth of Cut	2	1.87%	12.486	12.486	6.243	0.19	0.083
Feed Rate	2	0.62%	4.132	4.132	2.066	0.06	0.093
Residual Error	2	9.62%	64.086	64.086	32.043		
Total	8	100.00%	666.217				

It designates the signal to noise ratio, standard deviation and mean values of nine readings; which supporting a complete estimation of process inconsistency and stability [19]. The results deliver the statistical analysis which including ANOVA and identify the furthermost influencing input parameter for machinability of Inconel 825.Table 3 reported that the ANOVA outcomes for the responses established on the signal to noise ratio (S-N ratio), standard deviation and mean. The results inferred that the cutting speed is the most influencing input process parameter among the other two; the contribution of the S-N ratio, standard deviation and mean are 79.41%, 87.09% and 87.89% respectively. The influences of depth of cut and feed rate are suggestively minimum and indicated the lower impact on the responses. It is calculated through the delta values; which is the difference in the lowest and highest performance for all the input parameter. Form the table clearly indicates that the cutting speed is most influencing parameter for these three measures and followed by feed rate and depth of cut. Table 4 and Fig. 2, confirm that the rankings for the S-N ratio, standard deviation, and mean are A1B3C2, A1B3C2, and A1B2C3, respectively. This ranking emphasizes the ANOVA outcomes; additional confirmation for cutting speed is the most influences on machining responses during the turning of Inconel 825.

Table 4. Ranking for response

	S-N Ratio			Means			Standard deviation		
Level	Cutting Speed	Depth of Cut	Feed Rate	Cutting Speed	Depth of Cut	Feed Rate	Cutting Speed	Depth of Cut	Feed Rate
1	-2.869	-2.558	-2.597	203.8	217.2	217.7	220.9	229.8	231.0
2	-2.443	-2.451	-2.491	220.5	221.2	218.4	232.0	232.7	230.5
3	-2.139	-2.441	-2.363	233.9	219.8	222.1	240.6	231.1	232.1
Delta	0.731	0.117	0.233	30.1	4.0	4.4	19.7	2.9	1.6
Rank	1	3	2	1	3	2	1	2	3

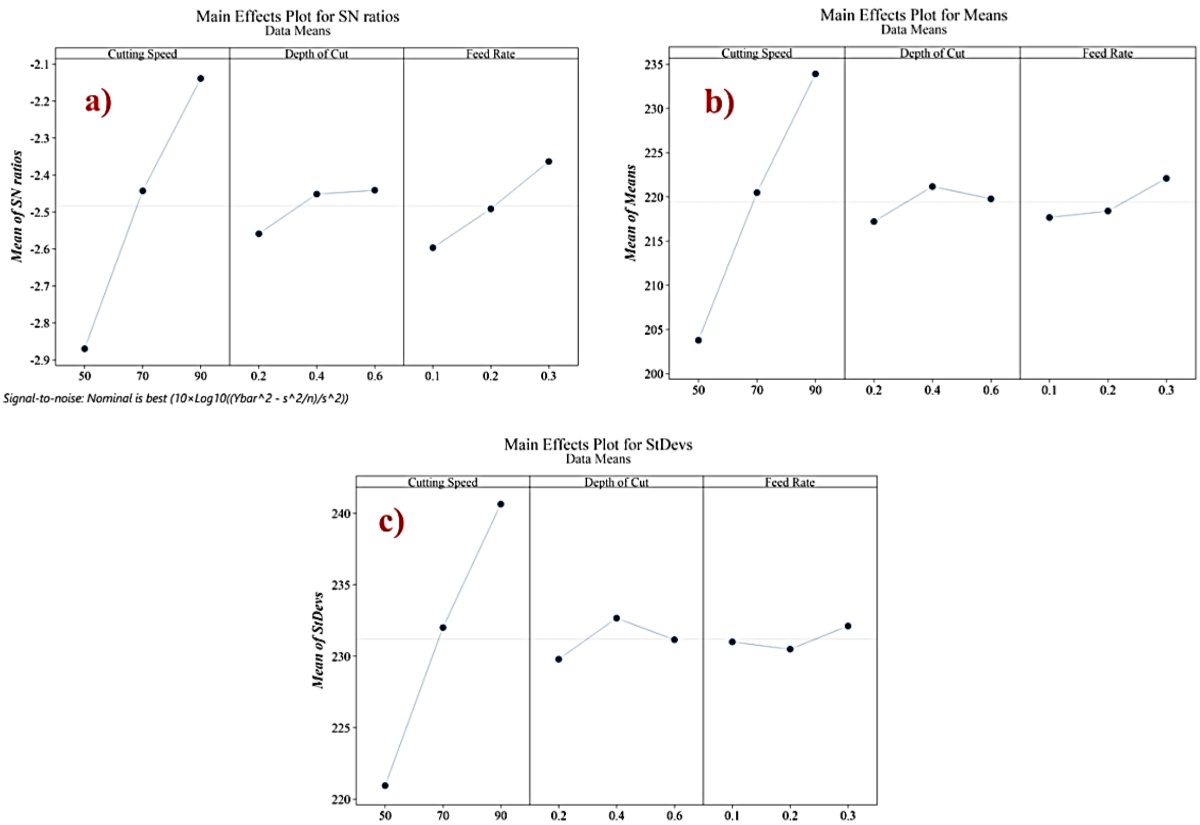

Fig. 2. Residual Analysis (a) S-N Ratio, (b) Means, and (c) standard deviation

These graphs are employed to authenticate the appropriateness of the Taguchi through the residual distribution. The outlines in the graph recommend that the residuals are follows the normal trend but randomly distributed; which indicates that the experimental findings are fits with the model and the designated parameter are statistically momentous [20]. It confirms the consistency of the experimental data and inference obtained from the Taguchi and ANOVA studies towards the turning of Inconel 825.

3.2 Results of Grey Relational Analysis

Grey relational analysis is often utilized in multi-response optimization situations. This method is based on the relationship between sequences, specifically their difference or similarity. This transforms multiple performances into a single grey relation grade for comparison and optimization. For larger the better as presented in Eq. (1).

$$x_i^*(k) = \frac{x_i(k) - min\, xi\,(k)}{max\, xi\,(k) - min\, xi\,(k)} \tag{1}$$

Where, $x_i(k)$: Original value of the k^{th} response for the i^{th} experiment, $x_i*(k)$: Normalized value,

min $x_i(k)$: Minimum value of the k^{th} response, max $x_i(k)$: Maximum value of the k^{th} response. When a lower value is better as shown in Eq. (2).

$$x_i^*(k) = \frac{max\, xi\,(k) - x_i(k)}{max\, xi\,(k) - min\, xi\,(k)} \tag{2}$$

The original sequence can be normalized by dividing all values by the series' first value if there is a target value to be reached. The following is an expression for the grey relational coefficient and can be written and given in Eq. (3).

$$\zeta_i(k) = \frac{\Delta_{min} + \zeta\Delta_{max}}{\Delta_i(k) + \zeta\Delta_{max}} \tag{3}$$

Where, $\xi_i(k)$: Grey Relational Coefficient (GRC) for the i^{th} experiment and k^{th} response, $\Delta_i(k)$ - $|x0*(k)-x_i*(k)|$: Absolute difference between the ideal normalized value and the actual normalized value, Δ_{min}: Minimum of all $\Delta_i(k)$ values, Δmax: Maximum of all $\Delta_i(k)$ values, ζ: Distinguishing coefficient. The GRC indicates how close a particular experimental result is to the ideal normalized result. The grey relational grade is can be written as and given in Eq. (4).

$$\gamma_i = \frac{1}{n}\sum_{k=1}^{n} \zeta_i(k) \tag{4}$$

where, γ_i: Grey Relational Grade (GRG) for the i^{th} experiment, n: Total number of performance characteristics, $\xi_i(k)$: Grey Relational Coefficient for the k^{th} response.

The GRG can also define as the weighted or unweighted mean of the GRCs for all the outcomes. It also supplies a single value on behalf of whole performance for multi objective optimization. The degree of influence that the comparison sequence can have on the reference sequence is shown by the grey relationship grade. The grey relational grade for the reference and comparison sequences would be higher than the other grey relational grades if the comparison sequence is considered to be more significant than the others [21, 22]. Table 5 shows the Sequence of grey relational analysis.

It inferred that the responses variation with respect to the cutting speed, feed rate, and depth of cut. Particularly, the higher cutting speed results in higher cutting forces and tool wear and also poor machinability of Inconel 825. The S-N ratio and standard deviation are providing the process stability and response consistency which supports and succeeding ANOVA and multi response optimization studies. Based on the observation, out of the 27 trials, the sixth trial ran is the ideal one. The maximum value of GRG is found to be 0.8721 for the input conditions. The optimal conditions for cutting at 50 m/min, 0.2 mm/rev feed rate, and 0.6 mm depth of cut which produced 3.52 µm surface roughness, 430.26 N cutting force, and 150.84 µm flank wear. A comparison sequence's grey relational grade associated with a reference would be greater than the further grey relational grade if that reference is deemed to be more essential than the others [23]. Fig. 3, shows the residual analysis for the outcomes such as flank wear, surface roughness and cutting force. These graphs are important in confirming the assumptions of randomness and normality in the experimental readings. It is follow the normal pattern and consistently distributed and also confirming noise in the random system [20]. This also support the statistical reliability of the model used in this work and confirms that the input process parameters with respect to the responses. Form figure confirm that the Taguchi are valid and the outcomes are reliable for decision making.

Table 5. Sequence of grey relational analysis

Sl. No	Cutting Speed (m/min)	Depth of Cut (mm)	Feed Rate (mm/rev)	SR (µm)	Cutting Force (N)	Flank wear (µm)	Grey Relational Coefficient (GRC)			Grey Relational Grade (GRG)	Rank
							Surface roughness	Cutting force	Flank wear		
1	50	0.2	0.1	2.54	428.36	152.63	0.5104	0.6666	0.904	0.6936	4
2	50	0.4	0.1	2.62	456.25	168.34	0.4881	0.582	0.8011	0.6238	10
3	50	0.6	0.1	2.86	480.61	175.06	0.7975	0.4182	1	0.7386	3
4	50	0.2	0.2	3.84	440.34	162.58	0.4343	0.7821	0.8206	0.679	5
5	50	0.4	0.2	4.15	449.54	172.65	0.5481	0.6524	0.8025	0.6677	7
6	50	0.6	0.2	3.52	430.26	150.84	0.7206	1	0.8957	0.8721	1
7	50	0.2	0.3	4.28	445.35	170.67	0.4038	0.7057	0.7642	0.6246	9
8	50	0.4	0.3	3.95	435.58	164.52	0.4589	0.8718	0.7028	0.6779	6
9	50	0.6	0.3	3.75	444.25	176.28	1	0.7212	0.829	0.8501	2
10	70	0.2	0.1	2.85	454.64	185.36	0.4248	0.5975	0.5385	0.5203	13
11	70	0.4	0.1	2.96	462.38	190.54	0.4739	0.5298	0.5289	0.5108	15
12	70	0.6	0.1	3.15	470.67	196.25	0.8811	0.4725	0.5623	0.6386	8
13	70	0.2	0.2	4.23	461.62	189.69	0.4001	0.5358	0.5052	0.4803	17
14	70	0.4	0.2	4.64	472.64	198.57	0.4495	0.4606	0.5018	0.4706	16
15	70	0.6	0.2	4.45	458.38	180.69	0.6514	0.5627	0.5732	0.5958	11
16	70	0.2	0.3	4.56	475.26	201.35	0.356	0.4457	0.5073	0.4363	21
17	70	0.4	0.3	4.05	463.52	191.25	0.4025	0.5211	0.4704	0.4647	19
18	70	0.6	0.3	3.92	471.36	199.65	0.7095	0.4682	0.4997	0.5592	14
19	90	0.2	0.1	3.46	495.25	218.62	0.3711	0.3577	0.3711	0.3666	25
20	90	0.4	0.1	3.59	486.54	215.36	0.4322	0.3914	0.3671	0.3969	23
21	90	0.6	0.1	3.74	502.64	230.54	0.6548	0.3333	0.4067	0.465	18
22	90	0.2	0.2	4.31	494.61	219.35	0.3333	0.36	0.3582	0.3505	26
23	90	0.4	0.2	4.51	501.83	222.36	0.3752	0.3358	0.3524	0.3545	24
24	90	0.6	0.2	4.48	475.67	203.57	0.5077	0.4435	0.388	0.4464	22
25	90	0.2	0.3	4.94	490.57	220.39	0.3465	0.375	0.3547	0.3588	27
26	90	0.4	0.3	4.51	479.31	206.68	0.624	0.4246	0.3333	0.4606	20
27	90	0.6	0.3	4.54	495.45	205.4	0.9952	0.4782	0.5165	0.5658	12

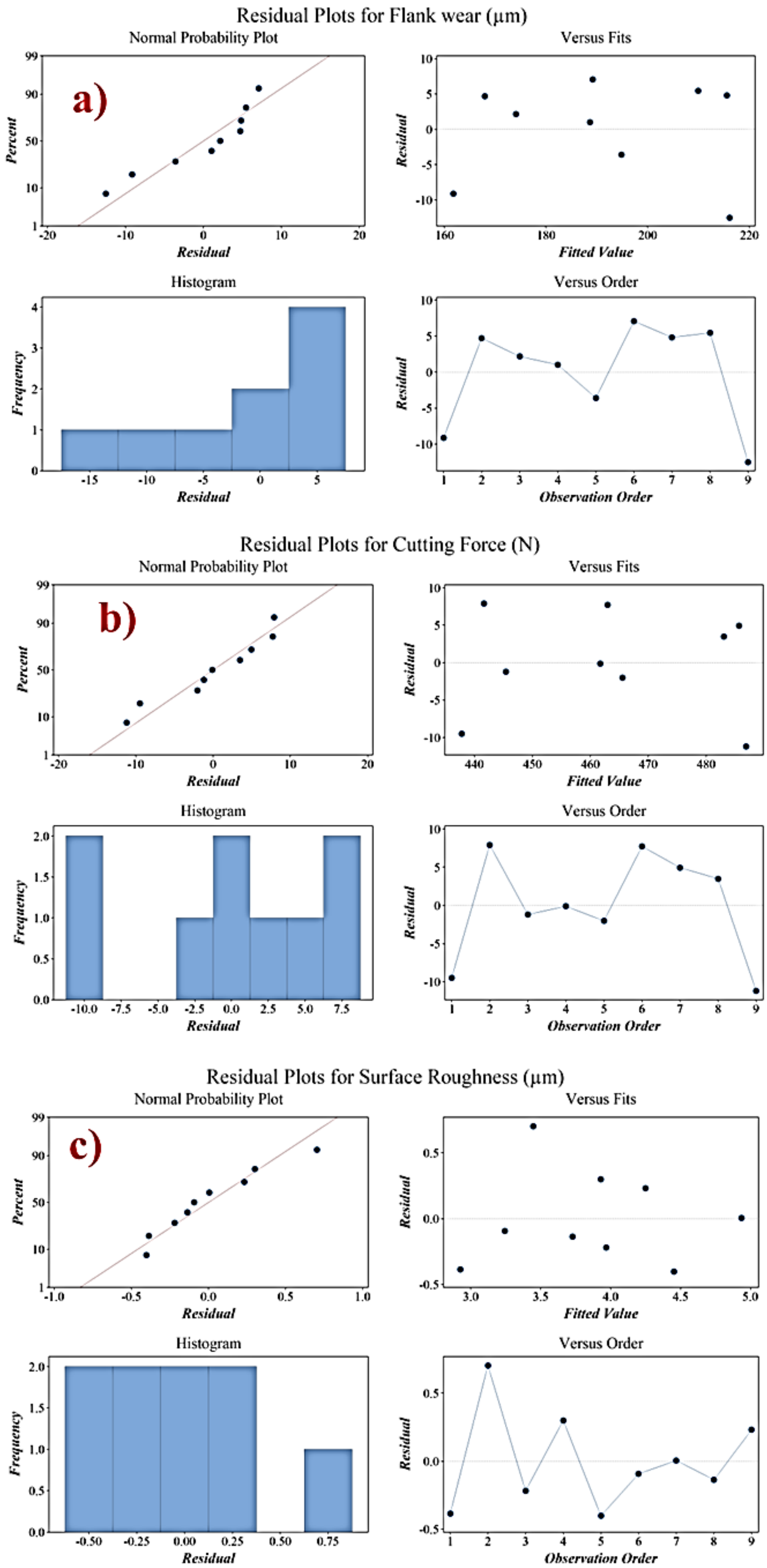

Fig. 3. Residual analysis (a) flank wear, (b) cutting force, and (c) surface roughness

3.3 Fuzzy Inference System

One important artificial intelligence technique that is well-known for its efficiency in managing intricate nonlinear systems is fuzzy logic. A more sophisticated and less ambiguous grey-fuzzy relational grade can be attained by applying fuzzy logic. The basic ideas behind fuzzy modeling are fuzzy set theory and language systems, which are designed to simulate the analysis of a human professional. The system for fuzzy inference is shown in Fig. 4. Eqs. (5) - (7) were obtained from grey relational analysis. Table 6 shows the regression analysis findings for the responses produced by the fuzzy inference system. Flank wear has the highest R^2 (89.54%) and adjusted R^2 (83.27%), confirming the prediction of tool wear based on input machining parameters. The cutting force has R^2 (88.40%) and an adjusted R^2 (81.44%), while surface roughness has lower R^2 (75.27%) and adjusted R^2 (60.44%). It confirms that the fuzzy model produces nonlinear interactions between the input parameter and responses [24]. Table 7 indicated that the minimum responses obtained from the input parameter such as cutting speed as 50, depth of cut as 0.2 and feed rate as 0.1.

$$\text{Flank wear } (\mu m) = 98.2 + 1.148 \text{ Cutting Speed} + 11.2 \text{ Depth of Cut} + 39.5 \text{ Feed Rat} \tag{5}$$

$$\text{Surface Roughness } (\mu m) = 1.333 + 0.02142 \text{ Cutting Speed} - 0.275 \text{ Depth of Cut} + 5.77 \text{ Feed Rate} \tag{6}$$

$$\text{Cutting Force (N)} = 379.6 + 1.089 \text{ Cutting Speed} + 8.4 \text{ Depth of Cut} + 21.3 \text{ Feed Rate} \tag{7}$$

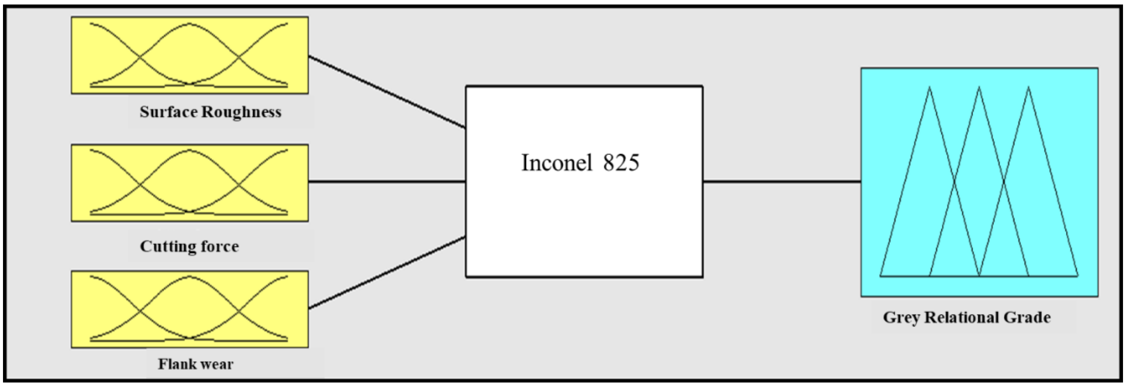

Fig. 4. Fuzzy inference system

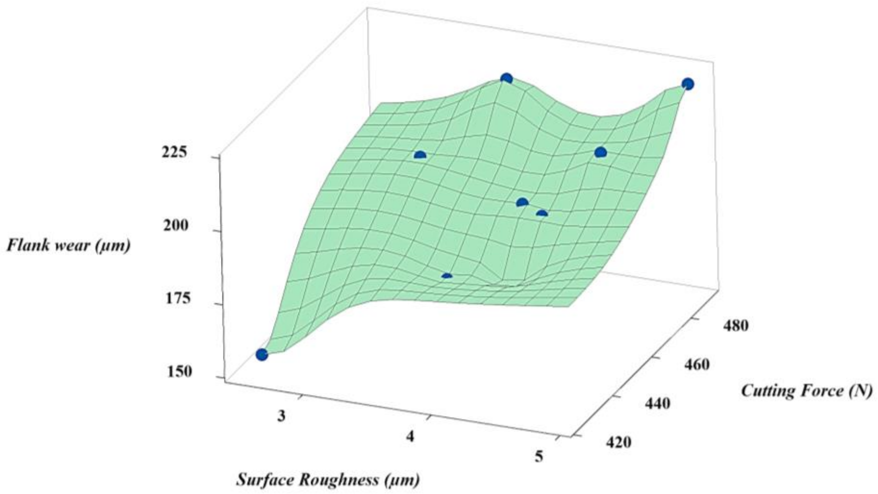

Fig. 5. Optimal Response Analysis

From Grey-Fuzzy logic optimal responses were arrived and the input parameter such as cutting speed as 50 m/min, feed rate as 0.1 mm/rev and depth of cut as 0.2 mm as revealed in Fig. 5. For these conditions the anticipated responses of surface roughness, cutting force, flank wear is 2.925

µm, 437.84 N, 161.76 µm, respectively. The composite desirability has a high level of optimization effectiveness (0.85067). The composite desirability has a high optimization effectiveness of 0.85067. This result demonstrates that the indicated input parameter drastically improved the Inconel 825 machining effectiveness.

Table 6. Response

Responses	R^2	R^2(adj)
Flank wear	89.54%	83.27%
Surface Roughness	75.27%	60.44%
Cutting Force	88.40%	81.44%

Table 7. Solution

Cutting Speed	50
Depth of Cut	0.2
Feed Rate	0.1
Flank Wear (µm)	161.758
Cutting Force (N)	437.842
Surface Roughness (µm)	2.92556
Composite Desirability	0.85067

3.4 PCA Analysis

PCA entails applying a statistical technique to simplify and gain a better understanding of big datasets. This method allows the evaluation of important components by converting associated machining features into a collection of independent components [12, 25]. Through this method, the multi-objective response matrix is subsequently built. Three principal components PC1, PC2, and PC3 have been determined using PCA. The variation is seen by the Eigen analysis of the correlation matrix in Table 8. Interestingly, it has been found that 63% of the variability may be explained by the first principal component alone. The Multi-Response Performance Index (MRPI) calculates each key component's unique weight based on its proportion of accountability.

Table 8. Eigen analysis of the Correlation Matrix

Principal Component	Eigenvalue	Variations (%)
First	1.8909	63
Second	0.8121	27.1
Third	0.2970	9.9

Table 9. Eigenvectors for principal components

Performance Characteristics	Eigenvectors			Contribution
	First Principal component	Second Principal component	Third Principal component	
Surface Roughness (µm)	0.433	-0.885	-0.168	0.1874
Cutting Force (N)	0.618	0.428	-0.660	0.3819
Flank Wear (µm)	0.656	0.182	0.733	0.4303

The eigenvectors of the principal components were obtained via PCA for the responses such as surface roughness, flank wear and cutting force as shown in Table 9. From these PCA has 63% of the total variance; which indicated the substantial role with the other responses. Flank wear has the maximum contribution of 0.656, followed by cutting force as 0.618 and surface roughness as 0.433. It recommends that the wear is the furthermost influential factor towards the machinability.

The contributions of the responses such as flank wear, cutting force and surface roughness are 43.03%, 38.19% and 18.74% respectively.

Table 10. Grey coefficient with principal component analysis

	Individual Principal components			
Trials	PC1	PC2	PC3	MRPI
1	0.096	0.255	0.389	0.739
2	0.092	0.222	0.345	0.659
3	0.150	0.160	0.430	0.740
4	0.081	0.299	0.353	0.733
5	0.103	0.249	0.345	0.697
6	0.135	0.382	0.385	0.902
7	0.076	0.270	0.329	0.674
8	0.086	0.333	0.302	0.721
9	0.187	0.275	0.357	0.820
10	0.080	0.228	0.232	0.540
11	0.089	0.202	0.228	0.519
12	0.165	0.180	0.242	0.588
13	0.075	0.205	0.217	0.497
14	0.084	0.176	0.216	0.476
15	0.122	0.215	0.247	0.584
16	0.067	0.170	0.218	0.455
17	0.075	0.199	0.202	0.477
18	0.133	0.179	0.215	0.527
19	0.070	0.137	0.160	0.366
20	0.081	0.149	0.158	0.388
21	0.123	0.127	0.175	0.425
22	0.062	0.137	0.154	0.354
23	0.070	0.128	0.152	0.350
24	0.095	0.169	0.167	0.432
25	0.065	0.143	0.153	0.361
26	0.117	0.162	0.143	0.423
27	0.133	0.241	0.159	0.533

The proportions of accountability were used to establish each primary component's weights [26]. The MRPI, which measures performance, was computed using this data. Higher MRPI values correspond to better results. The experiment with the lowest cutting force, flank wear, and surface roughness also produced the highest MRPI. The highest MRPI value observed in Table 10 is 0.902. The MRPI, designated as A1B2C3, provides the ideal parameter settings, which are 50 m/min for cutting speed, 0.2 mm/rev for feed rate, and 0.6 mm for cut depth. This yields 3.52 µm surface roughness, 430.26 N cutting force, and 150.84 µm flank wear.

3.5 Validation of Result

It has been machined and the best turning parameters have been determined, a verification test is needed to evaluate how accurate the analysis. The precision was predicted using confirmation studies, which showed a decrease in cutting force from 445.35 N to 430.26 N, a decrease in flank wear from 170.67 µm to 150.84 µm, and a decrease in surface roughness from 4.28 µm to 3.52 µm. Fig. 6, shows the Inconel 825 microstructure for the turning with optimal machining conditions. It is inferred that from the image the grain distribution are uniform and the nonexistence of significant surface defects [27]. This uniformity is imperative for the application in the aerospace and chemical industries which requires corrosion resistance and mechanical strength.

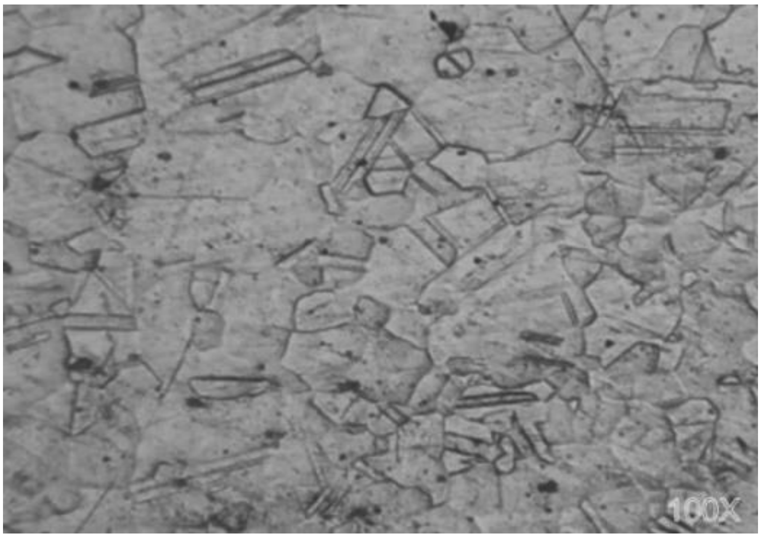

Fig. 6. Inconel' 825 microstructure

Table 11. Confirmation Test of GFRG and GPCA on the optimal level

Method	Surface roughness (μm)		Cutting force (N)		Flank wear (μm)	
	Predicted	Experimental	Predicted	Experimental	Predicted	Experimental
Grey A1B3C2	3.52	3.52	430.26	430.26	150.84	150.84
Fuzzy A1B1C1	2.92	2.54	437.842	428.36	161.758	152.63
PCA A1B3C2	3.52	3.52	430.26	430.26	150.84	150.84

Table 11 shows a comparison of the grey, fuzzy, and PCA models that predict Inconel 825 machining responses such as surface roughness, cutting force, and flank wear. The Grey and PCA methods match closely with the predicted and experimental findings and have higher accuracy with the optimum selection as A1B3C2. The ideal selection from the Fuzzy technique is A1B1C1, and the percentage deviation is substantial. The analysis using the Grey and PC approaches produces consistent predictions for the experimental settings. The limitation of the works is three input parameters were used in this study and tool coating not considered in this study.

5. Conclusions

This research work presented a cohesive optimization of Taguchi design, Grey-Fuzzy and PCA towards the machinability improvements. The followings findings were made from the experiment:

- Cutting speed is the most influencing parameter for all the three responses such as surface roughness, flank wear and cutting force.
- Grey-Fuzzy provides the distinguished estimation of multi responses and has superior GFRG of 0.882, which is compared to other technique. These values produced a surface roughness of 2.925 μm, a cutting force of 437.84 N, and flank wear of 161.76 μm.
- PCA assisted dimensionally enabled that the First PCA for 63% of the response inconsistency and the better multi response performance index as 0.902; which optimum process parameter as cutting speed 50 m/min, fees rate 0.2 mm/rev, and depth of cut 0.6 mm.
- A Grey and PCA method are closely agreements with the Predicted and experimental results and has higher accuracy with the optimum selection as A1B3C2. The optimum selection from Fuzzy approach as A1B1C1and has the percentage deviation is high. From the analysis Grey and PC methods yields the consistent predictions for the experimental conditions.

- This cohesive approach presented in this research work more reliable and better tactic for optimization the machining parameter and may use for other alloys in manufacturing industries.

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