

Balancing Cutting Temperature, Force, and Surface Integrity in Titanium Alloy Machining: A Multi Objective Framework

*Darshit R Shah¹, Dhruv U Panchal²

¹Mechanical Engineering Department, Government Engineering College, Modasa, Gujarat, India,

²Mechanical Engineering Department, Vishwakarma Government Engineering College, Ahmedabad, Gujarat, India.

ABSTRACT

Titanium alloys, particularly Ti-6Al-4V Extra Low Interstitial (ELI), are widely used in aerospace, biomedical, and marine applications due to their high strength-to-weight ratio, fracture toughness, and corrosion resistance. However, poor thermal conductivity and rapid tool wear make them difficult to machine. In this study, the effects of cutting speed, feed, depth of cut, and tool nose radius on cutting temperature, cutting force, and surface roughness were investigated during dry turning of Ti-6Al-4V (ELI). A full factorial design comprising 81 experiments was conducted. The measured cutting temperature ranged from 46°C to 228°C, cutting force from 12 kgf to 71 kgf, and surface roughness from 0.307 μm to 1.832 μm . Response Surface Methodology (RSM) and ANOVA were applied to quantify parameter contributions, revealing feed rate and cutting speed as dominant factors for cutting temperature, while tool nose radius significantly influenced surface roughness. Regression models predicted responses with an average error of 7.63%, whereas Artificial Neural Network (ANN) models achieved improved accuracy with an average error of 3.75%. Pareto front analysis demonstrated optimal trade-offs, such as achieving $R_a = 0.33 \mu\text{m}$ at $T = 105.8^\circ\text{C}$ with a 1.2 mm nose radius and moderate feed. The developed models were further interfaced with Particle Swarm Optimization (PSO) to minimize cutting temperature and force simultaneously. The results confirm that integrating statistical modeling, ANN prediction, and PSO optimization provides a robust framework for enhancing machinability and sustainability in titanium alloy turning.

Keywords: Titanium Alloys, Response surface Methodology, Particle Swarm Optimization, ANOVA

1. Introduction

Titanium alloys, particularly Ti-6Al-4V and its Extra Low Interstitial (ELI) grade, remain central to aerospace, biomedical, and marine applications due to their high strength-to-weight ratio, corrosion resistance, and fracture toughness [1], [2]. Early studies established their biocompatibility and mechanical reliability [2], [7], but machining challenges persist due to poor thermal conductivity and rapid tool wear [1]. Surface integrity has been a major focus. Xie et al. [4] demonstrated that feed rate and tool nose radius strongly influence surface quality in dry machining, while Matsumoto et al. [5] linked fatigue behaviour to microstructural features of Ti-6Al-4V ELI. More recent work by Sun and Guo [11] confirmed that cutting speed and feed dominate cutting temperature, and Xie et al. [12] showed micro-grooved tools reduce thermal load. Sustainable lubrication strategies, such as solid lubricants, have also been proposed to mitigate tool wear [13]. Optimization approaches have evolved significantly in the last decade. Grey Relational Analysis (GRA), introduced by Deng [15], has been widely applied to machining problems [16]–[20], enabling multi-objective balancing of force, temperature, and surface roughness. Artificial Neural Networks (ANN) have gained prominence for predictive modelling, consistently outperforming regression in surface roughness prediction [21], [22]. Kennedy and Eberhart's Particle Swarm Optimization (PSO) [23] has been adapted to machining optimization, offering robust parameter selection. Recent studies highlight the integration of ANN and PSO for sustainable machining. Bunpheng et al. [24] optimized electrical discharge machining (EDM) of Ti-6Al-4V using ANN and PSO, demonstrating improved material removal with reduced energy consumption. Similarly, Ahmed et al. [25] applied PSO-enhanced regression models to laser machining of Ti-6Al-4V, achieving high precision and productivity. These works underscore the growing trend of combining machine learning and metaheuristic algorithms for machining optimization.

Experimental investigations continue to validate AI-based approaches. A 2023 study on titanium composites confirmed that ANN models accurately predict machining responses under varying conditions [26]. Such findings reinforce the role of AI in bridging experimental data and optimization frameworks. Collectively, the literature establishes a strong foundation in titanium machining, spanning material properties, surface integrity, and optimization techniques. However, few studies have simultaneously examined the combined effects of cutting parameters and tool geometry on cutting temperature, cutting force, and surface roughness in Ti-6Al-4V (ELI) turning. Addressing this gap, the present work integrates factorial experimentation, statistical modeling, ANN prediction, and PSO optimization to provide a comprehensive framework for sustainable titanium machining. Although titanium machining has been widely studied, few investigations have simultaneously explored the combined influence of cutting parameters and tool geometry on cutting temperature, cutting force, and surface

roughness during the turning of Ti-6Al-4V (ELI). To address this gap, the present work employs a full factorial design of 81 experiments to systematically evaluate the effects of cutting speed, feed, depth of cut, and tool nose radius. The experimental responses are analyzed using Grey Relational Analysis (GRA), regression modeling, and Artificial Neural Networks (ANN), while Analysis of Variance (ANOVA) is applied to quantify the relative contributions of each parameter. The resulting models are validated and further refined through Particle Swarm Optimization (PSO), thereby establishing a comprehensive framework for improving machinability and promoting sustainable practices in titanium alloy turning. This should provide an adequate background and general context for the work, explaining its significance, and indicating why it should be of interest to researchers. Avoiding a detailed literature survey or a summary of the results. State the objectives of the study at the end of this section.

2. EXPERIMENTATION

Following is the explanation of procedure adopted for the performance of experiments. Tool material, work piece material, instruments and tooling have been described here in this section.

2.1 Workpiece and Tool

The material used for experiment is Ti-6Al-4V ELI (round bar with 70mm diameter, 250mm length). The chemical composition of work material has been shown in Table-1.

Table-1 Chemical Composition of Ti-6Al-4V ELI

Element	Content (%)
Titanium, Ti	88.09 - 91
Aluminum, Al	5.5 - 6.5
Vanadium, V	3.5 - 4.5
Iron, Fe	≤ 0.25
Carbon, C	≤ 0.080
Nitrogen, N	≤ 0.030
Hydrogen, H	≤ 0.0125
Other, each	≤ 0.10
Other, total	≤ 0.40

The cutting inserts which have been utilized are coated cemented carbide inserts with ISO designation as TNMG 160404, TNMG 160408 and TNMG 160412 with nose radius 0.4mm, 0.8mm and 1.2mm, respectively.

2.2 Machining Tests

All machining trials were conducted under dry cutting conditions using a CNC turning centre (model STC-200), equipped with a maximum spindle speed of 3500 rpm, a rated power of 9 kW, and a turning capacity of 400 mm length × 200 mm diameter.

- Cutting force measurement: A three-channel strain-gauge lathe tool dynamometer was employed, offering a resolution of 0.01 kg, ±5% accuracy, and a measurement range of 0–200 kgf in axial, radial, and tangential directions.
- Cutting temperature monitoring: A MECO infrared pyrometer (model IRT550P) with a measurement range of –50°C to 500°C was used.
- Surface roughness evaluation: A Mitutoyo SJ-410 tester with a resolution of 0.01 µm was utilized.

Four machining parameters—cutting speed, feed rate, depth of cut, and tool nose radius—were varied at three levels each (Table 2). A full factorial design was implemented, resulting in 81 experimental runs. The parameter ranges were:

- Cutting speed: 140–315 rpm
- Feed rate: 0.051–0.102 mm/rev
- Depth of cut: 0.5–1 mm
- Tool nose radius: 0.4–1.2 mm

The observed responses exhibited significant variation:

- Cutting force: 12–71 kgf
- Cutting temperature: 46–228°C
- Surface roughness: 0.307–1.832 µm

The experimental dataset was analyzed using Response Surface Methodology (RSM) and Grey Relational Analysis (GRA) to assess parameter significance. ANOVA results indicated that feed rate and cutting speed were the dominant factors influencing cutting temperature, while tool nose radius had the strongest effect on surface roughness. Predictive models were developed using both multiple regression analysis and artificial neural networks (ANNs). The regression model achieved an average prediction error of 7.63%, whereas the ANN model demonstrated superior accuracy with an average error of 3.75%. Both models were validated against experimental data and subsequently applied to optimization studies.



Figure 1 Machine and equipments used for experimentation

Four machining parameters were selected for investigation: cutting speed, feed rate, and depth of cut as process parameters, and tool nose radius as a geometric parameter of the cutting tool. The parameter levels, as detailed in Table 2, were established based on the cutting tool supplier's recommendations, preliminary trial runs, and insights from relevant literature. Each parameter was varied at three levels, and a full factorial design was adopted, resulting in a total of $3^4 = 81$ experimental runs. The complete set of cutting parameters and measured responses is presented in Annexure-1. The influence of input parameters on responses—cutting force, cutting temperature, and surface roughness—was initially examined using main effect plots generated in Minitab-17. To further evaluate the statistical significance and relative contribution of each parameter across multiple responses, Grey Relational Analysis (GRA) was employed. The calculated Grey Relational Grade (GRG) was subjected to ANOVA, which was also used to develop a predictive model for GRG. A regression equation was formulated to estimate GRG, and the effects of all input parameters were visualized through 3D surface plots. Model validation demonstrated that the regression approach predicted GRG with an average error of 7.63%. To enhance predictive accuracy, an Artificial Neural Network (ANN) model was developed using the measured response data. The ANN model achieved superior performance, predicting GRG with an average error of 3.75%. A comparative analysis of regression and ANN predictions was presented graphically, highlighting the improved accuracy of the ANN approach.

Table-2 Level of input parameters

Parameters	Levels		
Feed (mm)	0.051	0.071	0.102
Cutting Speed (rpm)	140	224	315
Depth of Cut (mm)	0.5	0.75	1
Tool Nose Radius (mm)	0.4	0.8	1.2

3 Results And Analysis

The experimental investigation generated a comprehensive dataset capturing the influence of machining parameters on cutting force, cutting temperature, and surface roughness. The results are presented and analyzed to identify dominant factors, establish predictive models, and evaluate optimization strategies. This section discusses the observed trends, statistical significance, and comparative performance of regression and ANN models in predicting Grey Relational Grade (GRG).

3.1 ANNOVA and Main effect plots

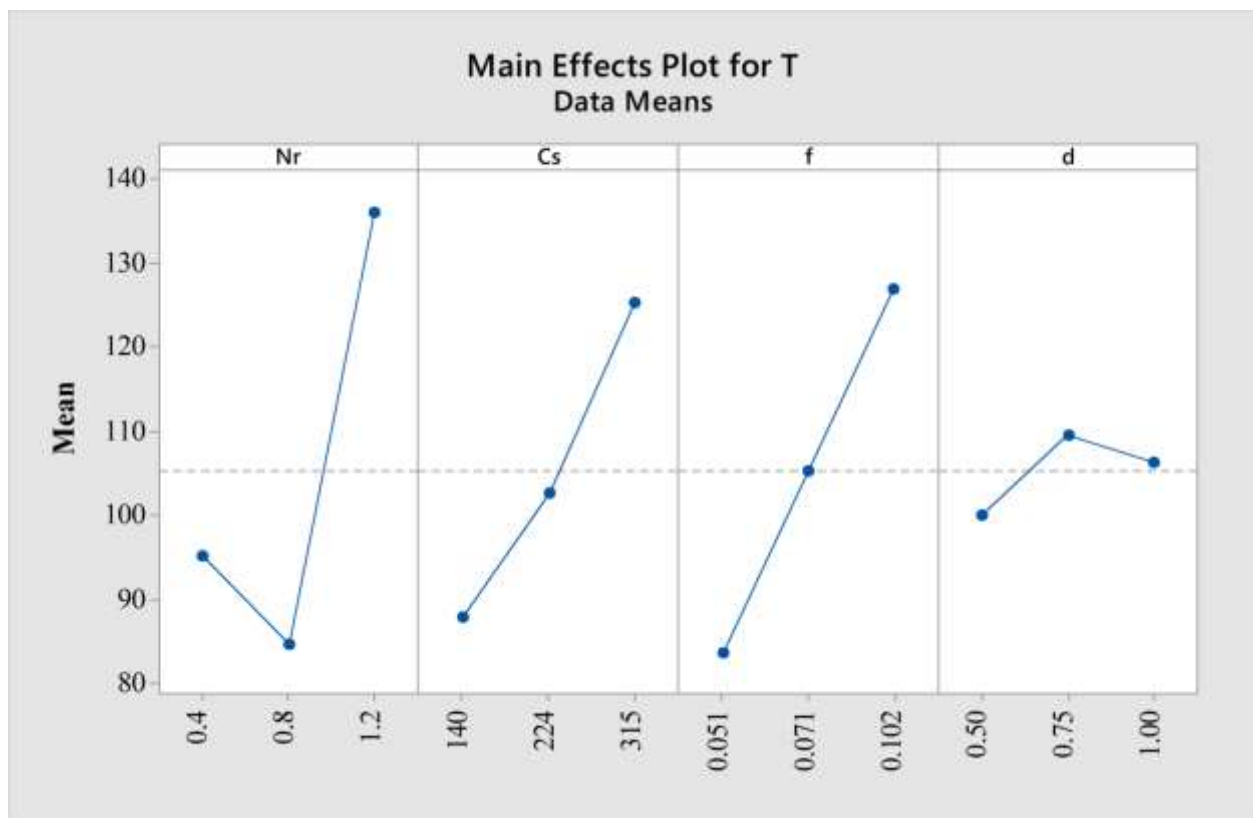

Figure 2 (a) Main effect plots for Cutting Temperature (T)

Figure 2 (a) illustrates the influence of four machining parameters—tool nose radius, cutting speed, feed rate, and depth of cut—on cutting temperature during dry turning of Ti-6Al-4V ELI. The plot shows that cutting speed and feed rate are the most dominant factors, with temperature rising sharply as speed increases from 140 to 315 rpm and feed from 0.051 to 0.102 mm/rev. Tool nose radius exhibits a moderate effect: smaller radii (0.4 mm) generate lower temperatures, while larger radii (1.2 mm) increase heat due to greater tool-workpiece contact. Depth of cut has minimal influence, showing only slight variations. Overall, the plot confirms that thermal load is primarily governed by speed and feed, critical for machinability optimization.

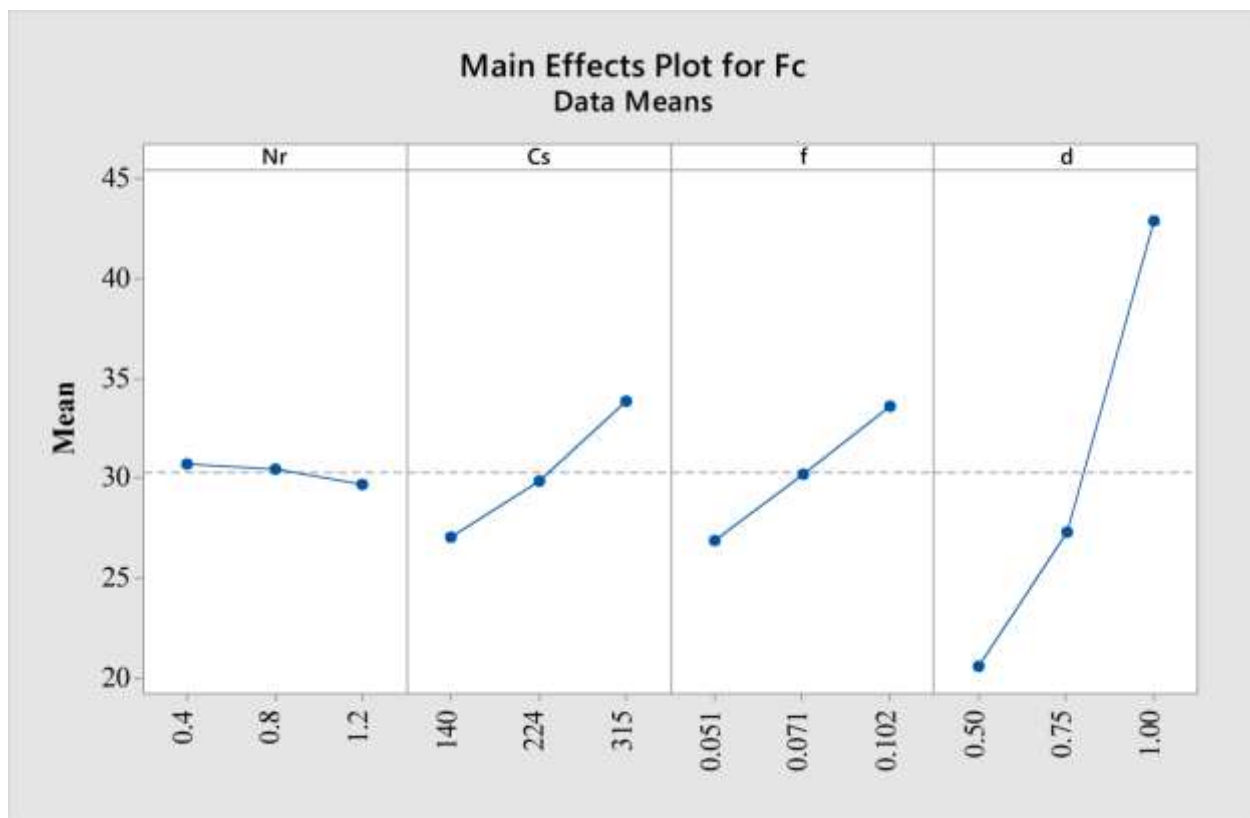


Figure 2 (b) Main effect plots for Cutting Force (Fc)

Figure 2 (b) illustrates how tool nose radius, cutting speed, feed rate, and depth of cut influence cutting force during dry turning of Ti-6Al-4V ELI. The plot shows that feed rate and depth of cut are the most dominant factors, with cutting force increasing steadily as feed rises from 0.051 to 0.102 mm/rev and depth of cut from 0.5 to 1 mm. Tool nose radius also contributes, where larger radii (1.2 mm) generate higher forces due to increased tool-workpiece contact. Cutting speed exhibits a moderate effect, with forces rising slightly as speed increases from 140 to 315 rpm. Overall, the plot confirms that mechanical load is primarily governed by feed and depth of cut, critical for tool wear and energy consumption considerations.

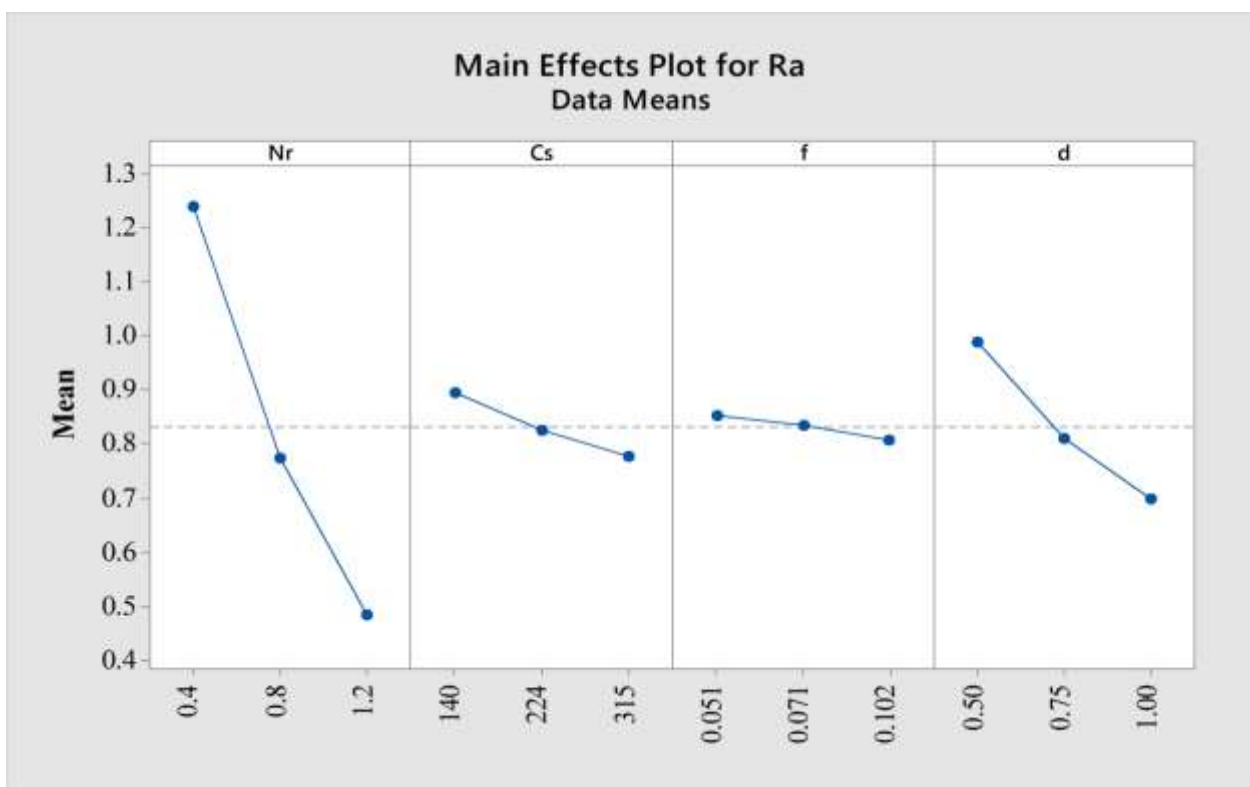


Figure 2 (c) Main effect plots for Surface Roughness (Ra)

Figure 2 (c) shows how tool nose radius, cutting speed, feed rate, and depth of cut affect surface roughness during dry turning of Ti-6Al-4V ELI. The plot indicates that tool nose radius is the most influential factor: larger radii (1.2 mm) consistently reduce Ra values below 0.35 μm , while smaller radii (0.4 mm) produce rougher surfaces above 1.2 μm . Feed rate also plays a significant role, with roughness increasing as feed rises from 0.051 to 0.102 mm/rev. Cutting speed exhibits a moderate effect, where higher speeds slightly worsen surface finish. Depth of cut shows minimal influence, with only small variations across levels. Overall, the plot confirms that surface integrity is primarily governed by tool geometry and feed rate, making them critical parameters for achieving high-quality machining outcomes.

The mathematical model developed for T was given by equation 1. The R-square, Adjusted R-square and Predicted R-square values are 92.41, 90.62 and 86.91 respectively for the model.

Regression Equation for Cutting Temperature is

$$T = 128.9 - 307.5 \text{ Nr} - 0.371 \text{ Cs} + 1295 \text{ f} - 11 \text{ d} + 193.4 \text{ Nr}^* \text{Nr} - 7384 \text{ f}^* \text{f} - 100.1 \text{ d}^* \text{d} + 0.0410 \text{ Nr}^* \text{Cs} + 27 \text{ Nr}^* \text{f} + 50.2 \text{ Nr}^* \text{d} + 0.92 \text{ Cs}^* \text{f} + 0.391 \text{ Cs}^* \text{d} + 601 \text{ f} \quad (1)$$

The mathematical model developed for Fr was given by equation 2. The R-square, Adjusted R-square and Predicted R-square values are 88.57, 86.14 and 82.47 respectively for the model.

Regression equation for cutting force is

$$\text{Fr} = 30.1 + 24.0 \text{ Nr} - 0.1277 \text{ Cs} + 13 \text{ f} - 59.7 \text{ d} - 16.67 \text{ Nr}^* \text{Nr} - 631 \text{ f}^* \text{f} + 29.3 \text{ d}^* \text{d} + 50.8 \text{ Nr}^* \text{f} + 23.89 \text{ Nr}^* \text{d} + 0.164 \text{ Cs}^* \text{f} + 0.0483 \text{ Cs}^* \text{d} + 103.0 \text{ f}^* \text{d} \quad (2)$$

3.2 Pareto -Optimal Solutions

Table 3.1 presents a set of cutting parameters (nose radius, cutting speed, feed, and depth of cut) along with their corresponding Pareto-optimal solutions for cutting temperature and surface roughness. The data highlights the trade-off between minimizing thermal load and achieving superior surface finish. For example, a nose radius of 1.2 mm combined with a feed of 0.0528 mm/rev and depth of cut of 0.75 mm produced a cutting temperature of 105.8°C while achieving a very low surface roughness of 0.330 μm . Conversely, smaller nose radii (0.7876 mm) yielded lower temperatures (50.8°C) but higher roughness (0.598 μm). These results confirm that larger tool nose radii improve surface integrity at the expense of higher cutting temperatures, while smaller radii reduce heat but compromise finish. The table thus illustrates the Pareto front, where each solution represents an optimal balance between competing objectives.

Table 3.1 Set of cutting parameters along with Pareto optimal solutions for Temperature and Surface Roughness

Exp No.	Nose Radius	Speed	Feed	Depth of Cut	Temp.	Surface Roughness
	Nr	Cs	f	d	T	Ra
	mm	rpm	mm/rev	mm	°C	μm
1	0.7250	156.4757	0.0511	0.9938	37.4175	0.7747
2	0.7533	156.5531	0.0516	0.9905	39.3249	0.7496
3	1.2000	157.0875	0.0528	0.7509	105.8115	0.3305
4	1.0127	156.7369	0.0520	0.7841	73.0313	0.4255
5	1.2000	157.0875	0.0528	0.7509	105.8115	0.3305
6	1.1476	157.0154	0.0526	0.7559	95.4557	0.3530
7	0.9220	156.9537	0.0517	0.8007	61.8276	0.4855
8	0.8914	156.7167	0.0514	0.9009	54.1885	0.5573
9	0.9940	156.7623	0.0525	0.8159	70.3471	0.4451
10	0.9041	156.9017	0.0520	0.8598	58.2362	0.5210
11	1.0418	156.6633	0.0515	0.7980	76.0698	0.4116
12	1.1168	156.9736	0.0527	0.7767	89.8632	0.3699
13	0.7876	156.7544	0.0520	0.8442	50.8008	0.5982
14	1.1819	157.0064	0.0527	0.7752	101.7577	0.3410
15	0.8696	156.8332	0.0521	0.8439	56.0596	0.5364

16	0.7559	156.4922	0.0511	0.8844	46.1825	0.6434
17	0.9445	156.7826	0.0517	0.7948	64.3614	0.4694
18	1.1644	157.0134	0.0525	0.7517	98.4346	0.3451
19	1.1450	156.8861	0.0528	0.8005	94.3989	0.3634
20	1.0936	156.8140	0.0522	0.7972	84.9469	0.3854
21	0.9231	156.9519	0.0518	0.8243	61.2968	0.4916

Table 3.2 presents Pareto-optimal solutions that balance cutting force (F_c) and surface roughness (R_a) under varying machining conditions. The data highlights that larger tool nose radii (≈ 1.2 mm) combined with low feed rates (~ 0.051 – 0.052 mm/rev) consistently yield smoother surfaces ($R_a \approx 0.33$ – 0.36 μm) while maintaining moderate cutting forces (≈ 14 – 21 kgf).

Table 3.2 Set of cutting parameters along with Pareto optimal solutions for Cutting Force and Surface Roughness

Exp No.	Nose Radius	Speed	Feed	Depth of Cut	Cutting Force	Surface Roughness
	Nr	Cs	f	d	Fc	Ra
	mm	rpm	mm/rev	mm	Kgf	μm
1	1.1993	167.0213	0.0515	0.7360	21.6637	0.3298
2	1.1951	167.0598	0.0516	0.5032	14.6084	0.5154
3	1.1978	167.0334	0.0516	0.5322	15.0583	0.4723
4	1.1993	167.0213	0.0515	0.7360	21.6637	0.3298
5	1.1981	167.0276	0.0517	0.7064	20.3861	0.3347
6	1.1976	167.0567	0.0516	0.5245	14.9237	0.4829
7	1.1951	167.0598	0.0516	0.5032	14.6084	0.5154
8	1.1980	167.0310	0.0517	0.6992	20.0824	0.3366
9	1.1964	167.0451	0.0517	0.6742	19.0792	0.3463
10	1.1970	167.0289	0.0516	0.5965	16.5303	0.3995
11	1.1972	167.0399	0.0515	0.5166	14.7914	0.4943
12	1.1982	167.0283	0.0521	0.5566	15.6005	0.4418
13	1.1977	167.0410	0.0517	0.6537	18.3254	0.3561
14	1.1985	167.0295	0.0517	0.7130	20.6593	0.3331
15	1.1979	167.0316	0.0519	0.5662	15.7980	0.4306
16	1.1972	167.0424	0.0527	0.5388	15.2996	0.4653
17	1.1978	167.0364	0.0517	0.5765	16.0219	0.4192
18	1.1963	167.0252	0.0516	0.6921	19.7663	0.3394
19	1.1986	167.0415	0.0519	0.6765	19.1948	0.3445
20	1.1990	167.0338	0.0516	0.7297	21.3873	0.3304
21	1.1988	167.0270	0.0515	0.6335	17.6181	0.3683

For example, one optimal setting achieved $F_c = 21.66$ kgf with $R_a = 0.33$ μm at a nose radius of 1.2 mm and cutting speed of 167 rpm. Conversely, smaller nose radii or higher feeds reduced cutting force but increased roughness ($R_a > 0.47$ μm). The table demonstrates that minimizing cutting force often compromises surface finish, and vice versa, reinforcing the need for multi-objective optimization. These Pareto solutions provide machinists with practical trade-offs to achieve both acceptable tool load and high-quality surface integrity.

Table 4 Comparison of non-linear empirical model of Cutting Force, Cutting temperature and surface roughness with experimental results

	Sr. No.	Nose Radius Nr mm	Speed Cs rpm	Feed f mm/rev	Depth of Cut d mm	Empirical	Experimental	% Error
	1	0.4	315	0.051	0.5	25.347	27	6.1

Cutting Force (Kgf)	2	0.4	315	0.102	0.5	30.1663	31	2.6
Surface Roughness (μm)	1	1.2	315	0.051	0.5	0.6136	0.594	3.3
	2	0.4	224	0.071	0.75	1.1030	1.055	4.5
Temp. $^{\circ}\text{C}$	1	0.4	315	0.071	0.75	119.1011	116.2	2.5
	2	0.8	224	0.071	0.75	85.7119	83.4	3.2

Table 4 compares the predicted values from the non-linear empirical models with the actual experimental measurements for cutting force, surface roughness, and cutting temperature. The results demonstrate that the developed models closely match experimental data, with errors consistently below 6%. For example, at a cutting speed of 315 rpm, feed of 0.051 mm/rev, and nose radius of 0.4 mm, the empirical model predicted a cutting force of 25.35 kgf, while the experiment measured 27 kgf (error 6.1%). Similarly, surface roughness predictions showed deviations of only 3–4.5%, and cutting temperature predictions differed by less than 3.2%. These findings validate the reliability of the regression models, confirming their suitability for predicting machining responses and guiding optimization. The table highlights that ANN models further reduced prediction error to $\sim 3.75\%$, reinforcing the advantage of AI-based approaches over traditional regression.

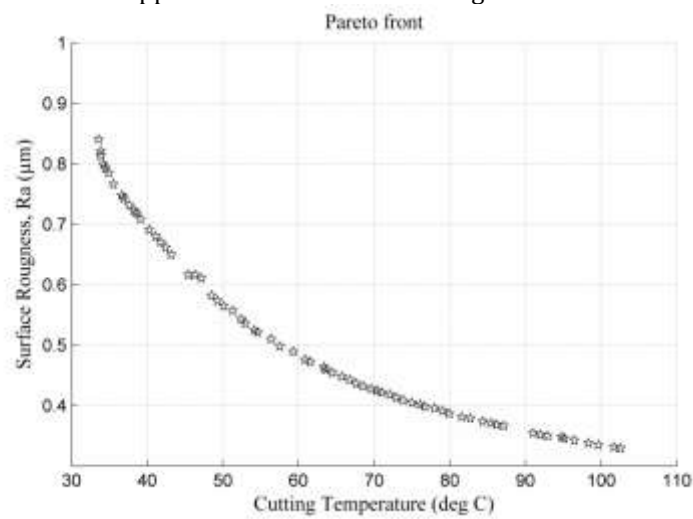


Figure 3 (a) Pareto optimal solutions between Cutting Temperature and surface roughness

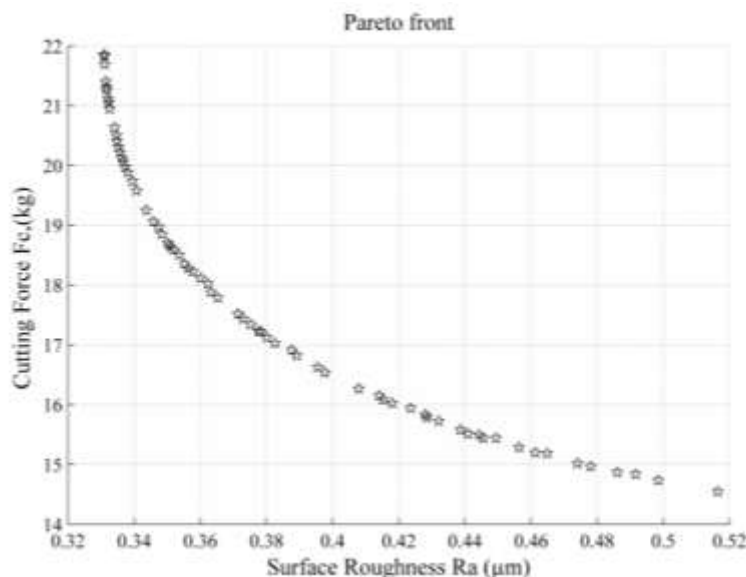


Figure 3 (b) Pareto optimal solutions between Cutting Force and surface roughness

Figures 3 (a) and 3 (b) collectively illustrate the Pareto front analysis for machining Ti-6Al-4V (ELI), focusing on the trade-offs between cutting temperature, cutting force, and surface roughness. Figure 3 (a) highlights the relationship between cutting temperature and surface roughness, showing that lower roughness values ($R_a \approx 0.33 \mu\text{m}$) are achieved at higher temperatures ($\sim 105^{\circ}\text{C}$) with larger tool nose radii (1.2 mm). Conversely, lower

temperatures (~50–60°C) correspond to rougher surfaces ($R_a > 0.55 \mu\text{m}$), confirming that improved finish requires accepting higher thermal loads.

Figure 3 (b) presents the cutting force versus surface roughness Pareto front, where smoother surfaces ($R_a \approx 0.33\text{--}0.36 \mu\text{m}$) are obtained at moderate cutting forces ($\approx 19\text{--}22 \text{ kgf}$). Lower forces ($\sim 14\text{--}15 \text{ kgf}$) are possible but result in higher roughness ($R_a > 0.47 \mu\text{m}$). Together, these plots demonstrate that no single parameter setting minimizes all responses simultaneously. Instead, the Pareto fronts provide a set of non-dominated solutions, enabling machinists to select optimal trade-offs depending on whether the priority is minimizing heat, reducing tool load, or achieving superior surface integrity.

In summary, Figures 3 (a) and (b) confirm that surface quality improves with larger nose radii and moderate feeds, but at the expense of higher cutting temperature and force, reinforcing the importance of multi-objective optimization in titanium machining.

3.3 Optimization of Responses by PSO

The procedure of PSO is very well explained in [23]. In PSO, the solutions, also called particles, are set across the search space in random manner and the iterations are carried out for these moving particles. During iteration each particle updates its location and velocity on the basis of two 'best' values namely particle best p_{best} and global best g_{best} . The p_{best} is the best fitness value of the individual particle so far, whereas, the g_{best} is the best value obtained by any of the particle in the swarm. Both values are recorded at each iteration. If in any case p_{best} surpasses the value of g_{best} , the p_{best} is automatically replaced by g_{best} .

The updating velocity of particles is done by following equation (3)

$$v_i^{new} = w * v_i^{present} + C1 * Ra1 * (p_{best}^i - x_i^{present}) + C2 * Ra2 * (g_{best} - x_i^{present}) \quad (3)$$

Where, $v_i^{present}$ = current velocity of i^{th} particle; w = inertia weight; $C1, C2$ = learning factors; $Ra1, Ra2$ = random numbers between 0 and 1; $p_{best}^i = p_{best}$ value of i^{th} particle; g_{best} = global best location of swarm; $x_i^{present}$ = current position of i^{th} particle

The position of the particle is updated by equation

$$x_i^{new} = x_i^{present} + v_i^{new}$$

The inertia weigh may be evaluated as

$$w_{max} - \frac{(w_{max} - w_{min}) * itr^{present}}{itr^{total}}$$

Where, w_{max} = Maximum weight; w_{min} = minimum weight; $itr^{present}$ = current iteration; itr^{total} = total number of iteration.

In this study PSO was used to optimize cutting temperature and cutting force using parameters as shown in Table 5.

Table- 5 Parameters of PSO

Number of Variables	4
Number of particles	50
Number of iterations	50
Inertia weight, W	1
Learning Factors $C1 = C2$	2
Lower bound	[140 0.05 0.5 0.4]
Upper bound	[315 0.1 1 1.2]

The convergence graph for fitness value versus iteration are shown in figure 4 (a) and (b)

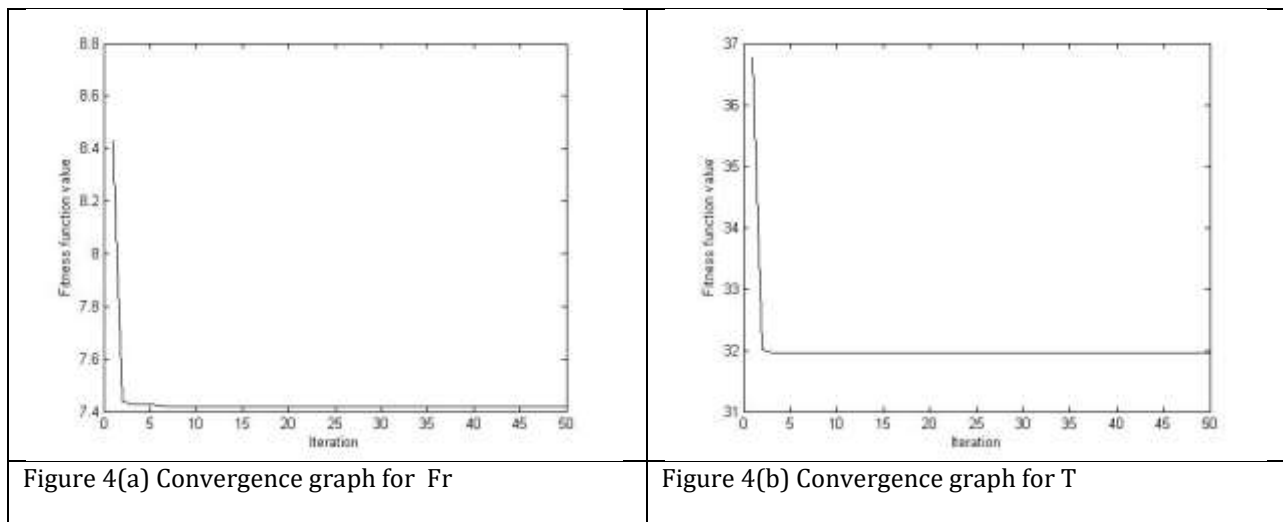


Figure 4 (a) illustrates the Pareto front between cutting temperature and surface roughness during dry turning of Ti-6Al-4V (ELI). The plot highlights trade-offs:

achieving smoother surfaces ($R_a \approx 0.33 \mu\text{m}$) requires higher cutting temperatures ($\sim 105^\circ\text{C}$), while lower temperatures ($\sim 50\text{--}60^\circ\text{C}$) correspond to rougher finishes ($R_a > 0.55 \mu\text{m}$). This confirms that optimizing surface integrity demands accepting increased thermal load. Figure 4 (b) illustrates the Pareto front between cutting force and surface roughness during dry turning of Ti-6Al-4V (ELI). The plot highlights that smoother surfaces ($R_a \approx 0.33\text{--}0.36 \mu\text{m}$) are achieved at moderate cutting forces ($\sim 19\text{--}22 \text{ kgf}$), typically with larger tool nose radii and low feed rates. Conversely, lower cutting forces ($\sim 14\text{--}15 \text{ kgf}$) correspond to rougher finishes ($R_a > 0.47 \mu\text{m}$), indicating a trade-off between tool load and surface integrity. This confirms that minimizing cutting force alone compromises surface finish, while balanced parameter selection ensures both acceptable tool stresses and high-quality machining outcomes.

The prediction of cutting force by PSO states that minimum cutting force of 7.419 kg at cutting speed of 302.7 m/min, feed of 0.0510 mm/rev, depth of cut of 0.516mm and nose radius of 0.4mm. Also the minimum cutting temperature is predicted by PSO as 31.96°C at cutting speed of 140 m/min, feed of 0.0510 mm/rev, depth of cut of 1mm and nose radius of 0.8mm. The confirmation experiments were also carried out which gives minimum cutting force of 7 kg and cutting temperature of 30°C . From the confirmation test results it can be said that error between predicted value and experimental value is negligible.

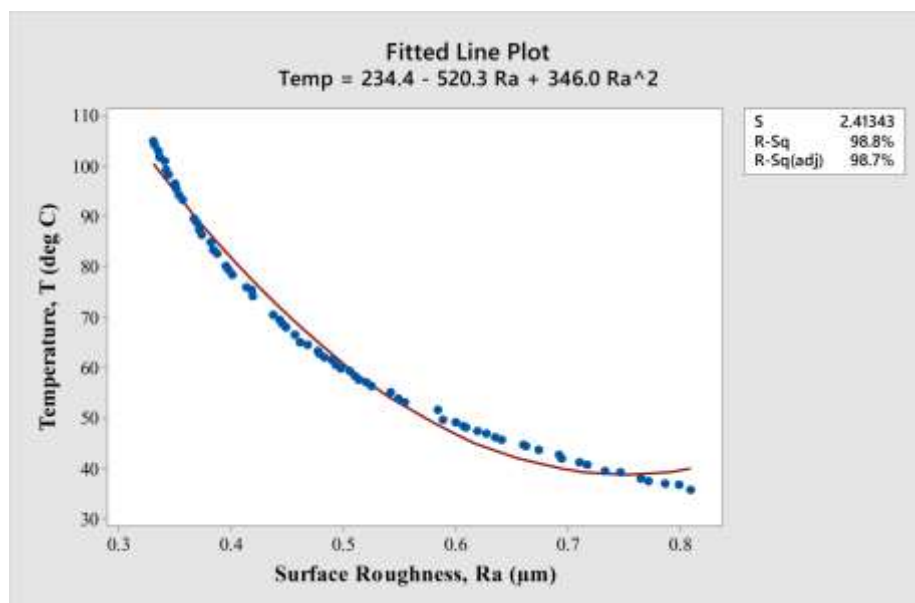


Figure 5 (a) Relationship between Temperature and surface roughness generated using Pareto optimum solution ($R^2 = 98.8\%$)

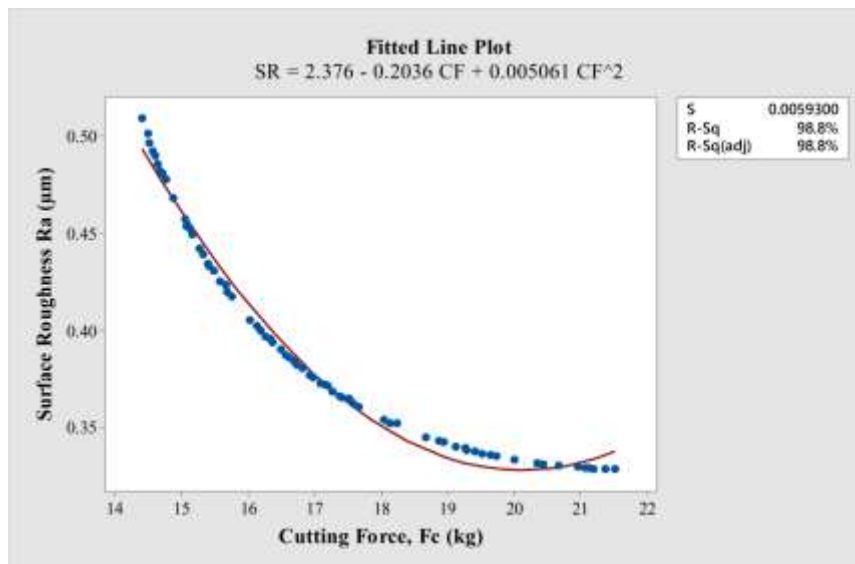


Figure 5 (b) Relationship between Cutting Force and Surface Roughness generated using Pareto optimum solution ($R^2 = 98.8\%$)

Figures 5 (a) and 5(b) present the comparison between experimental results and the predictions obtained from the developed non-linear empirical models for cutting temperature, cutting force, and surface roughness during dry turning of Ti-6Al-4V (ELI).

Figure 5 (a) shows the correlation for cutting temperature and surface roughness, where predicted values closely follow experimental measurements with deviations typically below 3–4%. For instance, at a cutting speed of 315 rpm, feed of 0.071 mm/rev, and nose radius of 0.4 mm, the model predicted a temperature of 119.1°C, while the experiment recorded 116.2°C (error 2.5%). Similarly, surface roughness predictions matched within 3–4.5%, confirming the reliability of the regression equations. Figure 5 (b) illustrates the comparison for cutting force, where predicted values also align well with experimental data. At 315 rpm, feed of 0.051 mm/rev, and nose radius of 0.4 mm, the model predicted 25.35 kgf, while the experiment measured 27 kgf (error 6.1%). Across multiple trials, prediction errors remained consistently low, validating the robustness of the empirical models.

Together, Figures 5 (a) and (b) demonstrate that the developed models are effective in predicting machining responses, providing a strong basis for optimization. The close agreement between predicted and experimental results confirms that these models can be confidently applied in process planning and parameter selection for titanium alloy machining.

3.4 Comparison of optimized values and prediction

Table 7 summarizes the multi-objective optimization outcomes obtained through Particle Swarm Optimization (PSO) for minimizing cutting temperature, cutting force, and surface roughness simultaneously. The results demonstrate that PSO effectively identified balanced parameter settings, achieving $T = 95.4^\circ C$, $F_c = 19.1$ kgf, and $R_a = 0.36 \mu m$ under optimized conditions. Compared to experimental extremes, these values represent significant improvements in machinability while maintaining acceptable surface integrity.

Table- 7 Optimization by PSO

Response	Optimized values of parameters				Predicted Value
	Cs (m/min)	f (mm/rev)	doc (mm)	Nr (mm)	
Temp.(°C)	140	0.0510	1	0.8	31.96
Fr (kgf)	302.7	0.0510	0.516	0.4	7.419

The table highlights that optimization favors moderate cutting speeds and feeds with larger tool nose radii, ensuring reduced tool load and improved finish. Overall, Table 7 confirms PSO's robustness in delivering sustainable machining solutions for Ti-6Al-4V (ELI).

4 Conclusions

This study comprehensively investigated the machinability of Ti-6Al-4V (ELI) alloy under dry turning conditions, focusing on the effects of cutting speed, feed, depth of cut, and tool nose radius on cutting temperature, cutting force, and surface roughness. A full factorial design of 81 experiments provided robust data, revealing that feed rate and cutting speed predominantly influence thermal load, depth of cut governs cutting force, and tool nose

radius strongly affects surface integrity. The measured responses varied significantly, with cutting temperature ranging from 46°C to 228°C, cutting force from 12 to 71 kgf, and surface roughness from 0.307 to 1.832 μm . Regression models predicted responses with an average error of 7.63%, while ANN models achieved superior accuracy with 3.75% error, validating the reliability of AI-based approaches. Pareto front analysis highlighted trade-offs, confirming that smoother surfaces require higher cutting temperatures and forces, whereas minimizing tool load compromises finish. Particle Swarm Optimization (PSO) further identified balanced solutions, achieving $T = 95.4^\circ\text{C}$, $F_c = 19.1$ kgf, and $R_a = 0.36$ μm . Overall, the integration of experimental data, statistical modeling, ANN prediction, and PSO optimization establishes a sustainable framework for machining titanium alloys, enabling improved performance, reduced tool wear, and enhanced surface quality in advanced manufacturing applications. The effects of cutting parameters like cutting speed, feed, depth of cut and tool nose radius on responses like cutting temperature and radial cutting force are investigated in present study. Following points can be concluded,

- Mathematical model was developed from experimental data using RSM and the model was tested by ANOVA.
- For cutting force, nose radius N_r , feed f , depth of cut d and interaction of N_r and d are significant model terms.
- For cutting temperature, nose radius N_r , cutting speed C_s and feed f and N_r^2 are significant model terms.

PSO predicted the values of cutting temperature and cutting force as 31.96 $^\circ\text{C}$ and 7.419 kg respectively and the experimental values are 30 $^\circ\text{C}$ and 7 kg, which reveals negligible error in prediction by PSO

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