

RESEARCH ARTICLE

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SUSTAINABLE DRY TURNING OF INCONEL 625: TAGUCHI–GRA WITH PARETO/KNEE ANALYSIS AND NSGA- II VALIDATION OF ENERGY, TOOL LIFE, SURFACE QUALITY, AND PRODUCTIVITY TRADE- OFFS

Fitim Zeqiri¹, Fatlume Zhujani*²

¹Department of Mechanical Engineering, Faculty of mechanical and computer engineering, University Isa Boletini, Mitrovica, Kosovo.

²Department of Mechanical Engineering, Faculty of mechanical engineering, University of Prishtina, Prishtina, Kosovo.

¹<https://orcid.org/0000-0002-7486-814X>, ²<https://orcid.org/0009-0009-2931-8040>

E-mail: fitim.zeqiri@umib.net, fatlume.zhujani@uni-pr.edu *

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ABSTRACT

Sustainable dry turning necessitates the reduction of energy intensity while maintaining production and quality. This research examines Inconel 625 under dry settings employing a Taguchi L9(3³) design (speed S, feed f, depth d) and a framework that integrates specific energy consumption (SEC) with tool life estimation, surface roughness, and material removal rate (MRR). The cutting power is calculated using the measured main cutting force F_c and kinematics; only F_c was documented, which represents the primary factor in cutting power during turning. Tool wear was quantified for each edge and converted into the expected tool life T_{pred} at VB* = 221 μm. Grey Relational Analysis (Set A: SEC↓, Ra↓, T_{pred}↑, MRR↑) yields a scalar ranking, whereas a continuous Pareto frontier in the (MRR, SEC) plane is established by sampling quadratic response surfaces throughout a dense grid and validated by Non-dominated Sorting Genetic Algorithm (NSGA II/ε constraint). The knee point is determined via the Kneedle method, which identifies the maximum distance. Results indicate: (i) feed predominantly influences Ra and tool life stress, whereas depth is the primary factor for MRR and SEC; (ii) the optimal GRA (s=50 m/min, f=0.08 mm/rev, d=1.0 mm) is situated near, yet within, the frontier; (iii) the unconstrained knee at MRR≈4.75 cm³/min and SEC≈0.002613 kWh/cm³ presents a well-balanced compromise. The integrated Taguchi–GRA–Pareto/knee methodology produces practical, energy-conscious parameter configurations for sustainable dry machining of Inconel 625.



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I. INTRODUCTION

Implementing sustainable methods that minimize resource consumption, save operating costs, and lessen environmental effect is becoming more and more important to the global industrial sector. Energy-efficient machining techniques are essential among the many facets of sustainable manufacturing, particularly in high-performance applications involving sophisticated materials. In particular, dry machining has become more popular because it can reduce operating costs and get rid of cutting fluids, which are frequently bad for the environment and human health [1], [2]. However, there are a lot of difficulties with the dry machining process, especially when dealing with materials like Inconel 625 that are hard to cut. Because of its exceptional mechanical strength, superior corrosion resistance, and capacity to maintain characteristics at high temperatures, this nickel-based superalloy finds extensive application in the aerospace, maritime, and chemical processing industries [3], [4]. Due to these same characteristics, it is notoriously difficult to machine, particularly in dry environments when the lack of cooling and lubrication can result in increased cutting pressures, poor surface smoothness, and rapid tool wear [5], [6]. In these situations, choosing the right cutting settings is essential to guaranteeing satisfactory machining results. Critical output measurements including cutting force, tool wear, surface roughness, and material removal rate (MRR) are greatly impacted by parameters like cutting speed, feed rate, and depth of cut, which must be carefully managed. Poor surface integrity, a shorter tool life, excessive energy consumption, and high production costs might result from improper parameter selection [7].

I.1 SUSTAINABLE DRY TURNING OF INCONEL 625

Sustainable Inconel 625 machining requires a careful balancing act between process efficiency and productivity. Cutting fluids play a major role in improving surface finish and tool life in traditional machining techniques. However, because of their disposal and mist production, cutting fluids pose serious health and environmental risks and make up a sizable amount of the overall cost of machining [8]. Therefore, if the difficulties can be successfully overcome, dry machining's removal of cutting fluids offers a feasible route to environmentally friendly production. Strategies for dry machining of alloys based on nickel have been studied recently. For example, a study [9] evaluated near-dry and dry turning of Inconel 718 and found that while dry cutting increased tool wear, improved settings helped reduce performance losses. The Taguchi method and Grey Relational Analysis (GRA) have been successfully combined to optimize several performance attributes at once in the context of sustainable dry turning of Inconel 625. This integrated approach, as noted in [10], makes it possible to determine the ideal cutting settings that strike a balance between efficiency and surface quality, supporting machining techniques that are ecologically friendly. Taguchi design and ANOVA can efficiently optimize machining parameters under various cooling conditions, as shown by Inconel 718 turning studies. This strategy supports sustainable production by lowering emissions, energy consumption, and tool wear while enhancing surface quality, as mentioned in [11].

I.2 MULTI-OBJECTIVE FRAMEWORK AND EXPERIMENTAL DESIGN

In order to investigate three controllable factors—cutting speed S (m/min), feed per revolution f (mm/rev), and depth of cut d (mm)—at three levels, dry turning experiments were set up using a Taguchi $L9(3^3)$ orthogonal array. The 3^3 full factorial (27 trials) is reduced to nine statistically balanced runs using the $L9$ design, which maintains orthogonality for objective main-effects estimation. Signal-to-noise ratios and main-effects graphs were used to analyze factor effects. Following testing, the various responses were normalized using Grey Relational Analysis (GRA) and combined into a single Grey Relational Grade (GRG) for parameter setting ranking; this Taguchi–GRA workflow is well-established in machining optimization [12–17]. The trade-off structure, however, can be concealed by any scalar ranking: settings with comparable GRG may inhabit quite distinct areas of the efficiency frontier. We fit quadratic response surfaces for MRR and SEC, sample a dense grid to create a smooth Pareto front in the (MRR, SEC) plane, and use the maximum-distance (Kneedle) rule to choose the knee point—the best-balanced compromise—in order to make the trade-offs clear. The frontier is validated using NSGA-II and an ϵ -constraint formulation to ensure robustness; MOGA offers a classical evolutionary substitute [18–24]. Pareto/knee + MOEA validation for explicit trade-off selection combined with Taguchi–GRA for ranking and factor understanding results in both interpretability and decision-readiness.

I.3 RESEARCH MOTIVATION AND OBJECTIVES

Motivation: Sustainable machining of Inconel 625 in dry conditions is both strategically significant and technically difficult. Removing cutting fluids lowers costs and environmental impact, but it also increases mechanical and thermal loads, accelerates tool wear, increases cutting forces, and jeopardizes surface integrity. Energy intensity (SEC), surface quality (R_a), tool life (T_{pred} at $VB^* = 221 \mu m$), and productivity (MRR) must all be addressed as combined objectives in optimization in order for it to be practical and provide useful parameter settings rather than just rankings. Manufacturers looking for energy-conscious advice to balance MRR, R_a , and T_{pred} in dry turning Inconel 625 without using cutting fluids are the ones driving this requirement. There is a gap in previous research, though, as Taguchi–GRA or multi-objective evolutionary algorithms (MOEAs) are frequently used in isolation. Few studies choose a knee point with algorithmic validation (e.g., NSGA-II/ ϵ -constraint), prioritize SEC as a primary objective, or map an explicit MRR–SEC Pareto front. By offering a knee-based proposal that converts the Pareto frontier into a single, defensible operational point for shop-floor decision-making, our study seeks to close this gap.

The objectives are as follows: (i) Use a Taguchi $L9(3^3)$ design to dry turn Inconel 625 and quantify the effects of cutting speed (S), feed rate (f), and depth of cut (d) on specific energy consumption (SEC), surface roughness (R_a), estimated tool life (T_{pred} at $VB^* = 221 \mu m$), and material removal rate (MRR). (ii) Determine the cutting power and SEC using the kinematics and measured tangential force (F_c) to support the $P \approx F_c \cdot v_c$ estimate for turning mechanical power. (iii) Use Set A ($SEC \downarrow$, $R_a \downarrow$, $T_{pred} \uparrow$, and $MRR \uparrow$) and Grey Relational Analysis (GRA) to determine high-performing parameter values and get a scalar ranking. (iv) Create a smooth MRR–SEC Pareto front, sample a dense grid, and fit quadratic response surfaces for MRR and SEC. (v) Use the Kneedle (maximum-distance) rule to identify the knee point and use the NSGA-II and ϵ -constraint procedures to validate the frontier. (vi) To determine when scalar ranking deviates from Pareto optimality, compare the GRA-best settings with the knee-point settings, offering energy-conscious, practical suggestions. (vii) Assign contributions of S , F , and D using Analysis of Variance (ANOVA) and Signal-to-Noise (S/N) ratios, connecting feed to R_a and wear rate/tool life and depth to MRR and SEC.

II. EXPERIMENTAL DESIGN

Figure 1 illustrates the experimental apparatus employed in this study, which comprises: (i) cutting insert, (ii) tool holder, (iii) three-component dynamometer for measuring F_c , F_f , and F_t , (iv) signal chain consisting of an analog-to-digital converter and data-acquisition card connected to a PC, (v) tool-wear inspection station (optical projector/microscope) for flank wear VB evaluation, and (vi) surface-roughness instrument with a contact probe, sensor, and analyzer for R_a measurement. Cutting power is determined from F_c and cutting speed v_c (see Section 2.3.1); SEC is obtained from energy and removed volume (refer to Section 2.3).

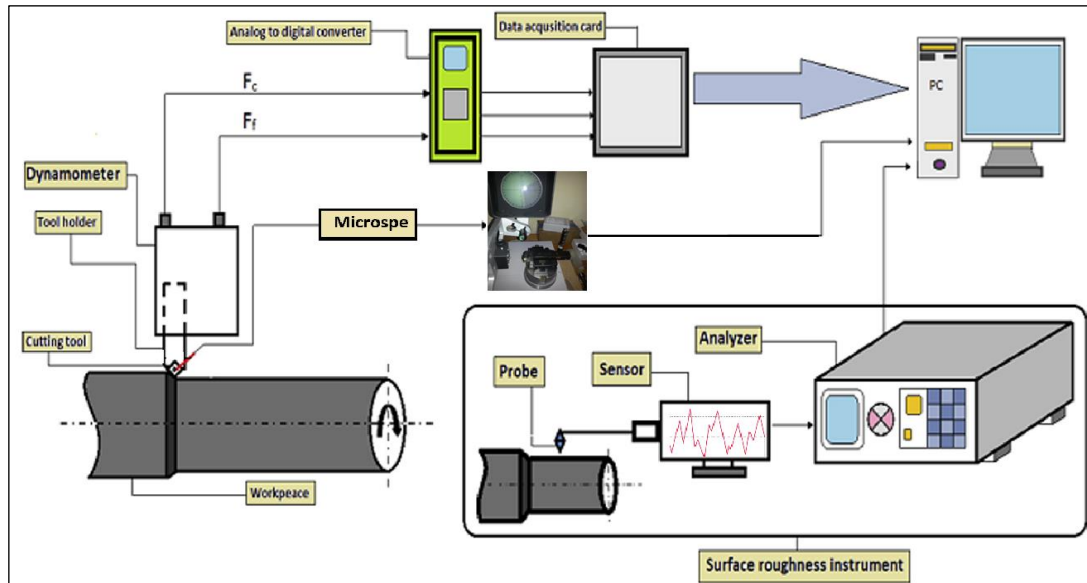


Figure 1: Experimental setup for dry turning of Inconel 625.
Source: Authors, (2026).

II.1 WORK MATERIAL, MACHINE, TOOLING, AND METROLOGY

Using a Pico Turn V-Turn 410 CNC lathe, round bars of Inconel 625 ($\varnothing 62 \text{ mm} \times 180 \text{ mm}$; Deutsche Nickel GmbH, EN 10204-3.1) with the composition listed in Table 1 were dry-turned. Every experiment was conducted on an all-g geared CNC lathe (Pico Turn V-Turn 410) without coolant. The cutting inserts were CNMG 120408NN, coated with PVD TiN/TiCN, fixed in an ISCAR PCLNR 2525 12A tool holder, on which a Kistler Type 5070A three-component dynamometer was mounted (Figure 2). Every run began with a new cutting edge. A Talysurf (Taylor Hobson) was used to quantify the surface roughness R_a (Figure 3). A TOOL MASTER 10 device (three-axis positioning) was used to monitor tool wear (Figure 4). Before measuring, the insert was cleaned of tiny particles using alcohol after each cut.

Table 1: Chemical composition and mechanical properties.

Chemical composition						Rm	HB
Ni [%]	Cr [%]	Mo [%]	Nb [%]	Fe [%]	Co [%]	N/mm ²	N/mm ²
59.64	22.34	9.20	3.57	4.20	0.032	470	223.229

Source: Authors, (2026).



Figure 2: Force measurement aperture Kistler Type 5070A.
Source: Authors, (2026).



Figure 3: Measurement of surface roughness with TALYSURF, TAYLOR HOBSON.
Source: Authors, (2026).



Figure 4: Equipment for measurement wear TOOL MASTER 10.

Source: Authors, (2026).

II.2 DESIGN OF EXPERIMENT (DOE)

II.2.1 Design and responses:

In order to assess SEC, Ra, T_{pred} (at $VB^* = 221 \mu\text{m}$), and MRR, dry turning was investigated using a Taguchi L9(3^3) array on three factors: cutting speed S, feed F, and depth of cut D, each at three levels. The 3^3 full factorial (27 trials) is compressed into nine orthogonal runs for unbiased main-effects estimations using the L9 design. Workpiece size, holder, overhang, and tool grade/geometry were all kept consistent during the dry tests. One replication was utilized for each treatment; runs were randomized; main-effects plots and S/N ratios were used to summarize factor effects; a confirmation run and pooled-error ANOVA (Section 4.1) were used.

II.2.2 Level Selection and Instrumentation:

Machine power and stiffness restrictions, tool-manufacturer recommendations for PVD-coated carbide while machining Inconel 625, and brief pilot cuts that confirmed stable dry turning without chatter or early edge failure were used to create parameter ranges. Every experiment was conducted using the same cutting length. A tri-axial dynamometer linked to a data-acquisition (DAQ) device was used to measure cutting forces. The three distinct levels for each factor were finalized through these pilot tests since generic models are unable to accurately relate input parameters, in-process signals, and output responses across all metal-cutting operations. Table 2 provides a summary of the resulting Taguchi L9(3^3) design and shows the experimental matrix for cutting speed S (m/min), feed rate F (mm/rev), and depth of cut D (mm) in both coded (levels 1–3) and natural units. There was a random run order. [25], [26].

Table 2: The coded experimental and natural matrix of the orthogonal array L9.

Exp No.	Coded matrix			Natural matrix		
	Abbreviation			S	F	D
	Unit			m/min	mm/rev	Mm
1	1	1	1	50	0.04	0.4
2	1	2	2	50	0.06	0.7
3	1	3	3	50	0.08	1.0
4	2	1	2	65	0.04	0.7
5	2	2	3	65	0.06	1.0
6	2	3	1	65	0.08	0.4
7	3	1	3	80	0.04	1.0
8	3	2	1	80	0.06	0.4
9	3	3	2	80	0.08	0.7

Source: Authors, (2026).

As indicated in Table 3, the workpiece was examined for surface finish, tool wear, and F_c .

Table 3: The orthogonal array L9's coded experimental and natural matrix for Ra, VB, and Fc

Exp. No.	Coded matrix			Natural matrix					
	Abbreviation			S	F	D	Ra	VB	Fc
	Unit			m/min	mm/rev	mm	µm	µm	N
1	1	1	1	50	0.04	0.4	0.911	215.33	260.14
2	1	2	2	50	0.06	0.7	1.595	232.21	478.31
3	1	3	3	50	0.08	1.0	1.573	348.24	687.93
4	2	1	2	65	0.04	0.7	1.174	253.22	383.37
5	2	2	3	65	0.06	1.0	1.542	356.13	622.56
6	2	3	1	65	0.08	0.4	2.092	253.34	419.92
7	3	1	3	80	0.04	1.0	0.884	361.36	460.55
8	3	2	1	80	0.06	0.4	1.355	265.57	342.28
9	3	3	2	80	0.08	0.7	2.345	371.02	642.74

Source: Authors, (2026).

II.3 MEASUREMENTS AND DERIVED QUANTITIES

Surface Roughness Ra was measured with a contact profilometer. A three-component lathe dynamometer was used to measure cutting forces in each trial. Cutting power was estimated using turning kinematics and the tangential force component, F_c . In particular, the cutting energy was derived from $E = P \cdot t$, where t is the net cutting time, and the cutting power was estimated as $P \approx F_c V_c$, where V_c is the cutting speed. The material removal rate (MRR) and cutting time, $V = \text{MRR} \cdot t$, were used to calculate the removed material volume. For longitudinal turning, MRR was calculated using geometric and kinematic relations. The key energy-intensity statistic, specific energy consumption (SEC), was initially defined as the ratio of cutting energy to removed material volume, or "SEC" = E/V . Following each run, tool wear was measured in terms of average flank wear, or VB. The expected tool life, " T_{pred} ," was calculated by extrapolating the measured wear to the selected flank-wear criterion "VB*=221" µm under the same cutting length because individual tool-life tests were not performed for every parameter combination. The complete formulations of MRR, energy, and SEC are provided in Section (2.3.1–2.3.3), along with the physical foundation for force decomposition and the rationale for use the tangential force in power calculation.

II.3.1 Force Measurement and Cutting Power Modeling

The tangential (F_c), feed (F_f), and radial (F_r) force components were measured by a three-component lathe dynamometer. The tangential component alone was used to calculate the cutting (chip-formation) power:

$$P_{\text{cut}} = F_c \cdot V_c \quad (1)$$

V_c is the cutting speed. $P = F \cdot V = F_c \cdot V_c + F_f \cdot V_f + F_r \cdot V_r$ is the mechanical power in turning. $F_r \cdot V_r = 0$ and $F_f \cdot V_f$ is insignificant in comparison to $F_c \cdot V_c$ since the radial velocity is practically zero ($V_r \approx 0$) and the feed velocity $V_f \ll V_c$. Therefore, the tangential force–speed product is used in industrial practice and machining textbooks to formulate spindle/cutting power [27-29]. Metric units:

$$P_{\text{cut}} [\text{kW}] = F_c [\text{N}] \cdot V_c [\text{m/min}] / 60 \quad (2)$$

II.3.2 Kinematics and Material removal rate (MRR)

Cutting speed is

$$V_c = \pi \cdot D \cdot N / 1000 [\text{m/min}] \quad (3)$$

The volumetric removal rate for longitudinal turning is

$$\text{MRR} = V_c \cdot f \cdot d [\text{cm}^3/\text{min}] \quad (4)$$

Equivalently $\text{MRR} = \pi D \cdot N \cdot f \cdot d$ in mm^3/min [30].

II.3.3 Energy and Specific Energy Consumption (SEC)

The cutting energy and removed volume for a net cutting time t (h) are

$$E = P_{\text{cut}} \cdot t [\text{kWh}] \quad (5)$$

$$V = \text{MRR} \cdot 60 t [\text{cm}^3] \quad (6)$$

because the precise amount of energy used is

$$SEC = E/V = P_{cut} / (60 MRR) \text{ [kWh/cm}^3\text{]} \quad (7)$$

The basic energy-intensity indicator used in sustainability evaluations to compare machining conditions is called SEC [31] [32].

II.3.4 Tool-Life Modeling and Wear (explanation of the VB criterion)

Following each run, tool wear was calculated using average flank wear VB. The expected tool life T_{pred} was calculated by extrapolating the measured wear to the adopted flank-wear criterion “VB*=221 μm ” for the same cutting length because a complete tool-life test was not conducted for each condition.

II.3.4.1 The Measurement

Run-to-failure life tests were not conducted by us. We employed a fresh cutting edge for every L9 condition and, following a single, steady-state pass, measured the flank-wear width (VB) on the primary cutting edge. Instead of measuring life directly, these single-pass wear snapshots were then used to anticipate the time (tool life) until a predetermined end-of-life criterion VB*.

II.3.4.2 Wear Criterion Selection VB* equals 221 μm .

Common machining standards and international practice for single-point tool-life testing (ISO 3685) use flank-wear thresholds in the 0.20–0.30 mm range as the end-of-life criterion for turning; lower values are usually used for finishing to preserve surface integrity and dimensional accuracy. We set VB* = 0.221 mm (221 μm), within the ISO-consistent finishing band [33] [34], in accordance with this recommendation and the finishing emphasis in dry turning of Ni-based superalloys.

II.3.4.3 Predicted Tool Life from Single-Pass Wear

Tool wear usually occurs in three stages: initial/running-in, steady, and accelerated. A near-linear law provides a good local approximation of tool wear during a brief, stable segment [35–37]. The anticipated time to reach VB* is obtained using the local wear rate $\dot{VB} \approx VB_i/t_i$ with measured VB_i after a duration t_i :

$$T_{pred} = (VB^* / VB_i) \cdot t_i. \quad (8)$$

II.3.4.4 Convention for Reporting

The term "tool life" in the results refers to the estimated time to attain VB* = 221 μm using Eq. (8); it is not a run-to-failure observation. SEC is used as a volume-normalized measure of energy intensity in both Pareto and knee-point analyses, where its explicit trade-off with MRR defines energy-aware operating compromises, and Grey Relational Analysis, where it is minimized along with surface roughness while productivity and tool life are maximized.

III. A FRAMEWORK FOR PROCESS OPTIMIZATION WITH MULTIPLE OBJECTIVES

Inconel 625 dry turning involves conflicting goals, such as maximizing material removal rate and tool life while decreasing specific energy consumption and surface roughness. A two-stage multi-objective optimization framework is used to handle these trade-offs. In order to rank discrete parameter combinations, various replies are first normalized using Grey Relational Analysis (GRA) in accordance with the Taguchi L9 design. These responses are then combined into a single Grey Relational Grade (GRG). Although it offers an effective screening and ranking system, the Taguchi-GRA method does not clearly reveal trade-off relationships between competing goals. Thus, the explicit trade-off frontier between material removal rate and specific energy consumption is constructed and analyzed using Pareto-based optimization with the Non-dominated Sorting Genetic Algorithm II (NSGA-II) and the ϵ -constraint approach. In this context, NSGA-II offers a continuous, dominance-based view of the solution space while GRA offers a scalar decision measure for discrete experimental settings. Together, these features allow for both informed compromise selection and comparison ranking. The Pareto-based optimization utilizing NSGA-II and the ϵ -constraint formulation is presented in Section 3.2, while Section 3.1 describes the Grey Relational Analysis process used for multi-response normalization and ranking.

III.1 GREY RELATIONAL ANALYSIS (GRA)

The Taguchi L9 testing findings were multi-response optimized using Grey Relational Analysis (GRA). First, each response's desired characteristic was used to normalize it to the interval [0,1]: For surface roughness (Ra) and specific energy consumption (SEC), lower is preferable [31];

$$R_a^* = \frac{\max R_a - R_a}{\max R_a - \min R_a'} \quad (9)$$

$$SEC' = \frac{\max SEC - SEC}{\max SEC - \min SEC'} \quad (10)$$

And for material removal rate (MRR) and projected tool life (T_{pred}), the larger the better,

$$T_{pred}^* = \frac{T_{pred} - \min T_{pred}}{\max T_{pred} - \min T_{pred}'} \quad (11)$$

$$MRR^* = \frac{MRR - \min MRR}{\max MRR - \min MRR'} \quad (12)$$

Next, grey relational coefficients were calculated as

$$\xi_i(k) = \frac{\Delta_{\min} + \zeta \Delta_{\max}}{\Delta_i(k) + \zeta \Delta_{\max}}, \quad (13)$$

Using $\zeta=0.5$ as the differentiating coefficient. The unweighted mean of the coefficients was used to calculate the Grey Relational Grade (GRG), a scalar metric for rating distinct cutting-parameter combinations. To prevent subjective bias and to guarantee a neutral aggregation of energy, quality, tool-life, and productivity objectives at the screening step, equal weights were given to each response in the GRG computation.

$$\text{GRG}_i = \frac{1}{m} \sum_{k=1}^m \xi_i(k), \quad (14)$$

III.2 PARETO-BASED MULTI-OBJECTIVE OPTIMIZATION AND KNEE-POINT IDENTIFICATION

The Non-dominated Sorting Genetic Algorithm II (NSGA-II) was used in a Pareto-based multi-objective optimization process to explicitly describe the trade-off between specific energy consumption (SEC) and material removal rate (MRR) [18]. If a solution $x^{(1)}$ is strictly better in at least one objective and not worse in any of the others, it is said to dominate another solution $x^{(2)}$. To produce a well-distributed approximation of the Pareto front, NSGA-II uses crowding-distance assignment and rapid non-dominated sorting. The goals of this study were to maximize MRR and minimize SEC. A further ε -constraint formulation was used for validation, where SEC was minimized subject to a minimum productivity requirement, "MRR" $\geq \varepsilon$ [23–24]. In order to extract the non-dominated set, quadratic response-surface models for SEC and MRR were fitted as functions of cutting speed, feed, and depth of cut and sampled on a dense grid. Additionally, a direct dominance screening was performed on the experimental L9 runs.

IV. RESULTS AND DISCUSSIONS

In addition to the derived responses—predicted tool life (T_{pred}), material removal rate (MRR), and specific energy consumption (SEC)—Table 4 presents the experimental results from the Taguchi L9 trials, including the measured tangential cutting force (F_c), flank wear (VB), and surface roughness (R_a). These findings serve as the foundation for the analyses that follow. To quantify factor effects, the individual answers in Table 4 are first analyzed using signal-to-noise ratios and analysis of variance (ANOVA) Section 4.1. The same dataset is then used for Pareto-based trade-off analysis and knee-point detection between MRR and SEC Section 4.3, as well as multi-response aggregation using Grey Relational Analysis Section 4.2.

Table 4: L9 responses.

Run	RPM	S (m/min)	F (mm/rev)	D (mm)	Time (h)	VB (μm)	Tool life (h)	Tool life (min)	Tool li (km)	MR R (cm^3/min)	SEC (kWh/ cm^3)	Ra (μm)
1	265	50.0	0.04	0.4	0.0314	215.3	0.032	1.934	0.513	0.8	0.0046	0.911
2	265	50.0	0.06	0.7	0.0209	232.2	0.020	1.193	0.476	2.1	0.0032	1.596
3	265	50.0	0.08	1.0	0.0157	348.2	0.001	0.598	0.317	4.0	0.0024	1.573
4	345	65.0	0.04	0.7	0.0242	253.2	0.021	1.267	0.436	1.82	0.0038	1.174
5	345	65.0	0.06	1.0	0.0161	356.1	0.001	0.599	0.31	3.9	0.0029	1.514
6	345	65.0	0.08	0.4	0.0121	253.3	0.010	0.633	0.436	2.08	0.0037	2.092
7	425	80.0	0.04	1.0	0.0196	361.4	0.012	0.719	0.306	3.2	0.0032	0.884
8	425	80.0	0.06	0.4	0.0131	265.6	0.011	0.654	0.416	1.92	0.0040	1.355
9	425	80.0	0.08	0.7	0.0098	371.0	0.006	0.35	0.298	4.48	0.0032	2.345

Source: Authors, (2026).

Due to differences in cutting speed and feed rate, the actual cutting length each wear snapshot varies even though the axial turning length is the same in all L9 trials. As a result, worn photos don't match a set cutting length.

IV.1 ANOVA OF FACTOR EFFECTS

A response-specific interpretation of factor importance and statistical significance is given by the ANOVA data compiled in Table 5. The depth of cut has the largest percentage contribution to specific energy consumption (SEC) and is statistically significant ($p < 0.05$), suggesting that material engagement is the primary determinant of energy intensity. According to its kinematic role in surface creation, feed rate is the primary and statistically significant factor ($p < 0.05$) for surface roughness (R_a). Feed rate and cutting speed have the biggest effects on expected tool life (T_{pred}) and are both statistically significant ($p < 0.05$), indicating their combined impact on wear rate and thermal loading.

The L9 design's zero error variance prevented formal significance testing, although the depth of cut and feed rate are the most important parameters for material removal rate (MRR), indicating their geometric control over volumetric output. The multi-response ranking in Section 4.2 and the energy–productivity trade-off analysis in Section 4.3 are supported by these response-specific trends (Minitab® Statistical Software, 2018).

Table 5: Summary of ANOVA factor contributions and significance across responses.

Response	Dominant factor (% contrib.)	Second factor (% contrib.)	Third factor (% contrib.)	Statistically significant factors ($p < 0.05$)
Ra (S/N, STB)	F (83.47%)	D (10.81%)	S (4.46%)	F
T _{pred} (S/N, LTB)	F (53.06%)	S (35.79%)	D (10.44%)	S, F
MRR (S/N, LTB)	D (54.69%)	F (31.09%)	S (14.22%)	*—
SEC (S/N, STB)	d (71.02%)	F (25.73%)	S (2.02%)	F, D

Source: Authors, (2026).

Note: Statistically significant factors are identified at the 95% confidence level ($p < 0.05$). For the material removal rate (MRR), the error sum of squares is zero due to the unreplicated L9 orthogonal array; therefore, F- and p-values are not reported and factor importance is inferred from percentage contribution. ANOVA computations were performed using Minitab® Statistical Software (Version 18).

IV.2 GREY RELATIONAL ANALYSIS

The Taguchi main-effects plots of the Grey Relational Grade (GRG) under equal weighting, derived from the GRA results in Table 6, are displayed in Figure 5. The ideal factor levels for the combined response set are indicated by the greatest mean GRG at S₁ (50 m/min), F₁ (0.04 mm/rev), and D₃ (1.0 mm). These patterns align with the ANOVA results in Section 4.1 (Table 5), which show that depth of cut is the main factor influencing productivity and energy intensity while feed rate is dominating for surface roughness and tool-life response. Thus, in the discrete L9 design space, the Taguchi–GRA optimum is the best overall compromise and is used as a reference for the continuous Pareto-front analysis shown in Section 4.3.

Table 6: Grey Relational Analysis; with $\zeta = 0.5$.

Run	S	F	D	SEC	Ra	T _{pred} (h)	MRR	GRC_SEC	GRC_Ra	GRC_T _{pred}	GRC_MRR	GRG	Rank
1	50	0.04	0.4	0.004578	0.911	0.032227	0.800	0.3333	0.9644	1.0000	0.3333	0.6578	2
2	50	0.06	0.7	0.003190	1.596	0.019891	2.100	0.5825	0.5064	0.5168	0.4360	0.5105	7
3	50	0.08	1.0	0.002415	1.573	0.009964	4.000	1.0000	0.5146	0.3721	0.7931	0.6700	1
4	65	0.04	0.7	0.003822	1.174	0.021121	1.820	0.4346	0.7158	0.5430	0.4089	0.5256	6
5	65	0.06	1.0	0.002893	1.514	0.009991	3.900	0.6935	0.5369	0.3724	0.7603	0.5908	4
6	65	0.08	0.4	0.003708	2.092	0.010555	2.080	0.4555	0.3768	0.3784	0.4340	0.4112	9
7	80	0.04	1.0	0.003215	0.884	0.011987	3.200	0.5748	1.0000	0.3946	0.5897	0.6398	3
8	80	0.06	0.4	0.004042	1.355	0.010901	1.920	0.3993	0.6080	0.3822	0.4182	0.4519	8
9	80	0.08	0.7	0.003227	2.345	0.005837	4.480	0.5712	0.3333	0.3333	1.0000	0.5595	5

Source: Authors, (2026).

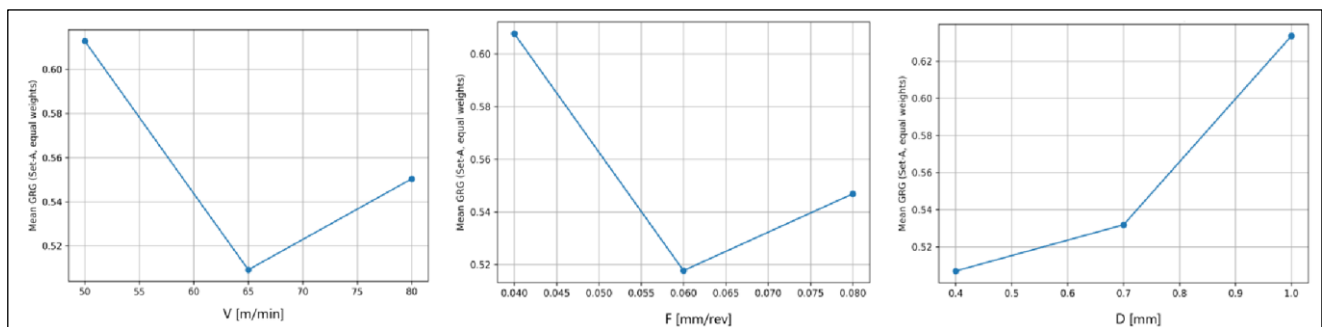


Figure 5: Taguchi main effects plots with equal weighting for Grey Relational Grade (GRG).

Source: Authors, (2026).

IV.3 PARETO-FRONT CONSTRUCTION AND KNEE-POINT DETECTION

While GRA provides a single ranking for discrete Taguchi settings, it does not directly depict the trade-off between competing goals. To visualize and analyze the energy–productivity compromise, Section 4.3 builds a smooth MRR–SEC Pareto front.

IV.3.1 Pareto Efficiency Analysis (MRR–SEC)

A smooth, unconstrained Pareto front built in the (MRR, SEC) plane, where productivity is maximized and energy intensity is minimized, is contrasted with the empirical Pareto set derived from the L9 tests in Figure 6. Two non-dominated solutions (Runs 3 and 9) are found from the discrete Taguchi trials, demonstrating the limited resolution of trade-off analysis when only experimental points are taken into account. Quadratic ridge response-surface models for MRR and SEC were fitted as variables of cutting speed, feed, and depth of cut in order to investigate the continuous design space. A smooth Pareto front was then generated by sampling on a dense parameter grid. The resulting frontier shows a monotonic trend, as shown in Fig. 6, indicating that increases in the rate of material removal are followed with higher specific energy consumption. Beyond the discrete L9, this smooth representation permits future knee-point identification and decision-oriented optimization.

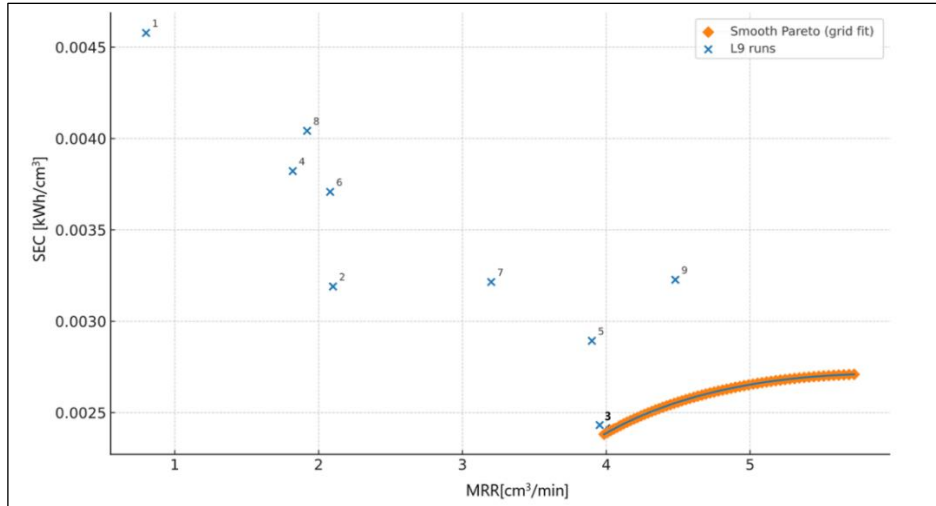


Figure 6: Smooth (unconstrained) Pareto front versus empirical L9.
Source: Authors, (2026).

In order to highlight surface quality and endurance, we also looked at a limited front using the illustrative parameters $Ra < 1.5 \mu\text{m}$ and $T_{\text{pred}} > 0.012 \text{ h}$. When tougher quality or life targets are applied, constraints quantify the productivity penalty by shifting the frontier higher or left (lower MRR for the same SEC).

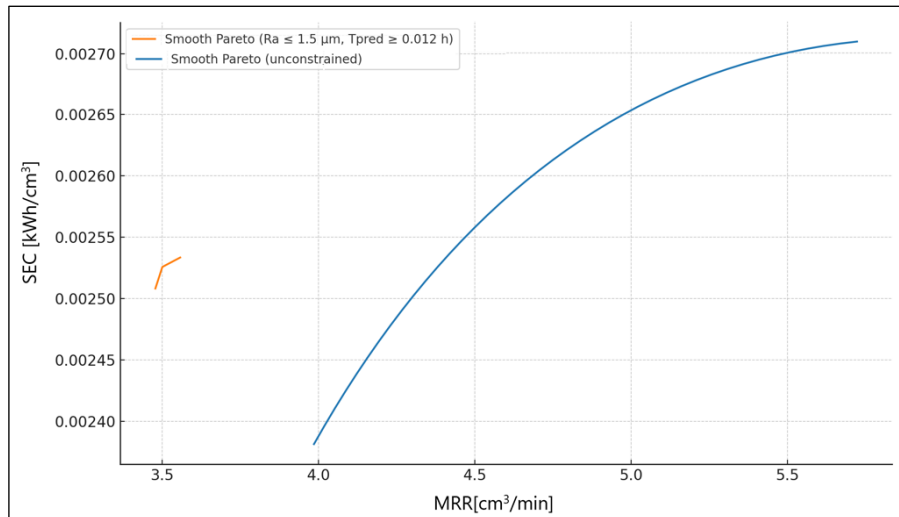


Figure 7: Constraint-free and constrained smooth Pareto front ($Ra \leq 1.5 \mu\text{m}$; $T_{\text{pred}} \geq 0.012 \text{ h}$).
Source: Authors, (2026).

IV.3.2 Knee-Point Selection on Unconstrained and Constrained Pareto Fronts

The maximal-distance positions from the chord joining each front's terminals are known as knee points. Figure 8: Unconstrained smooth Pareto front with knee point (maximal-distance criterion) in the (MRR, SEC) plane. The confined front under $Ra < 1.5 \mu\text{m}$ and $T_{\text{pred}} > 0.012 \text{ h}$ is depicted in Figure 9. A nearly balanced trade-off between productivity (MRR) and energy intensity (SEC) is offered by the knee.

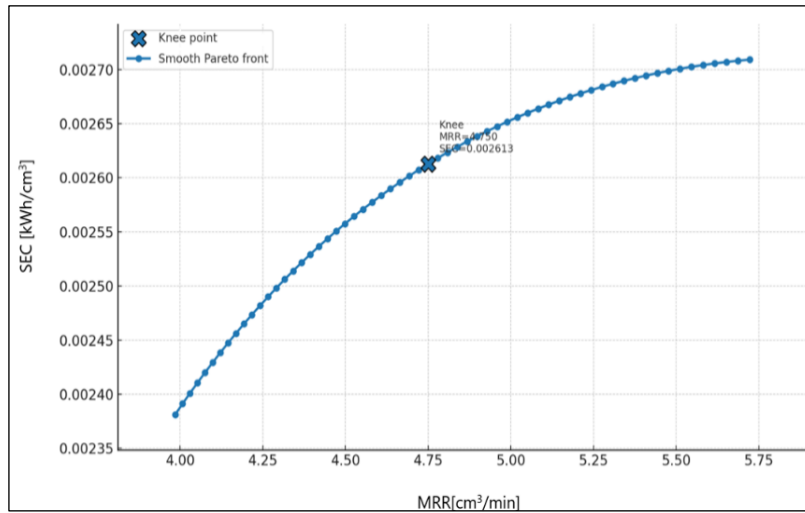


Figure 8: Unconstrained smooth Pareto front with knee point (maximal-distance criteria) in the (MRR, SEC) plane.
Source: Authors, (2026).

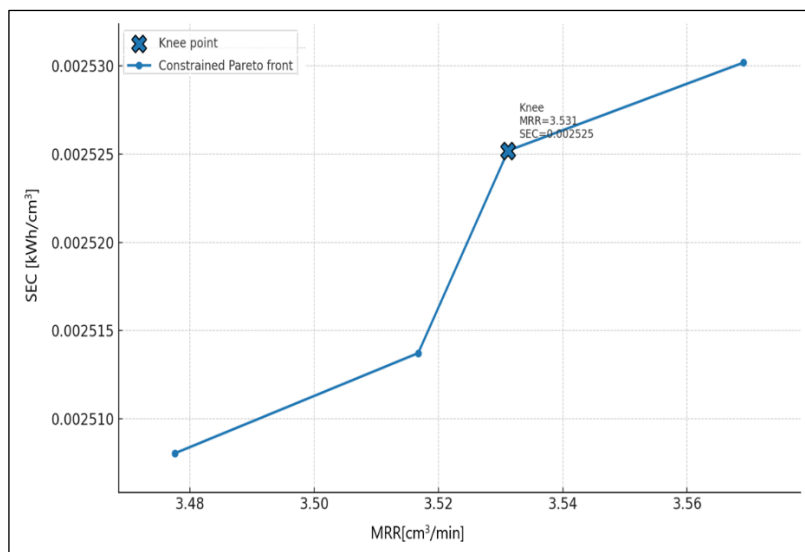


Figure 9: Pareto front with knee constraint ($Ra \leq 1.5 \mu\text{m}$, $T_{\text{pred}} \geq 0.012 \text{ h}$).
Source: Authors, (2026).

The confined knee increases energy intensity by $\Delta\text{SEC}=0.000059 \text{ kWh/cm}^3$ (2.3%) but decreases productivity by $\Delta\text{MRR}=1.860 \text{ cm}^3/\text{min}$ (39.2%) in comparison to the unconstrained knee ($\text{MRR}=4.750 \text{ cm}^3/\text{min}$, $\text{SEC}=0.002613 \text{ kWh/cm}^3$). The associated parameters change to $S=50 \text{ m/min}$, $f=0.051 \text{ mm/rev}$, $d=0.99 \text{ mm}$ from $S=65 \text{ m/min}$, $f=0.080 \text{ mm/rev}$, $D=1.00 \text{ mm}$. The knee occurs close to $S \approx 65 \text{ m/min}$, $f \approx 0.08 \text{ mm/rev}$, and $d \approx 1.0 \text{ mm}$ for the unconstrained front. The knee moves toward lower MRR and somewhat higher SEC under quality/life limitations (e.g., $Ra < 1.2 \mu\text{m}$ and $T_{\text{pred}} > 0.015 \text{ h}$), indicating the productivity penalty of more stringent criteria (see Figures 8-9). Figure 9: Constrained smooth Pareto front ($Ra \leq 1.2 \mu\text{m}$, $T_{\text{pred}} > 0.015 \text{ h}$) constructed similarly to Figure 8; knee point determined using the same rule to show a balanced operating point under life and quality limitations.

IV.3.3.GRA vs. Pareto knee

The knee point indicates a balanced operating condition in the MRR–SEC trade-off space, while the GRA-selected solution, as seen in Fig. 10, is near the rebuilt Pareto frontier. Run 3 ($S = 50 \text{ m/min}$, $F = 0.08 \text{ mm/rev}$, $D = 1.0 \text{ mm}$) is ranked as the best of the discrete L9 tests by the Taguchi–GRA technique (Set A, equal weights). It achieves a low specific energy consumption ($\text{SEC} = 0.002415 \text{ kWh/cm}^3$) at a moderate material removal rate ($\text{MRR} = 4.00 \text{ cm}^3/\text{min}$). This solution does not fall within the region of greatest trade-off sensitivity, despite being close to Pareto-optimal. The Pareto knee is a compromise point when any productivity gains would result in a disproportionately greater energy cost. It is located at $\text{MRR} = 4.75 \text{ cm}^3/\text{min}$ and $\text{SEC} \approx 0.002613 \text{ kWh/cm}^3$. This comparison shows that Pareto knee analysis offers supplementary, decision-oriented insight by locating a balanced operating point along the continuous energy–productivity trade-off, whereas GRA is useful for ranking discrete parameter values.

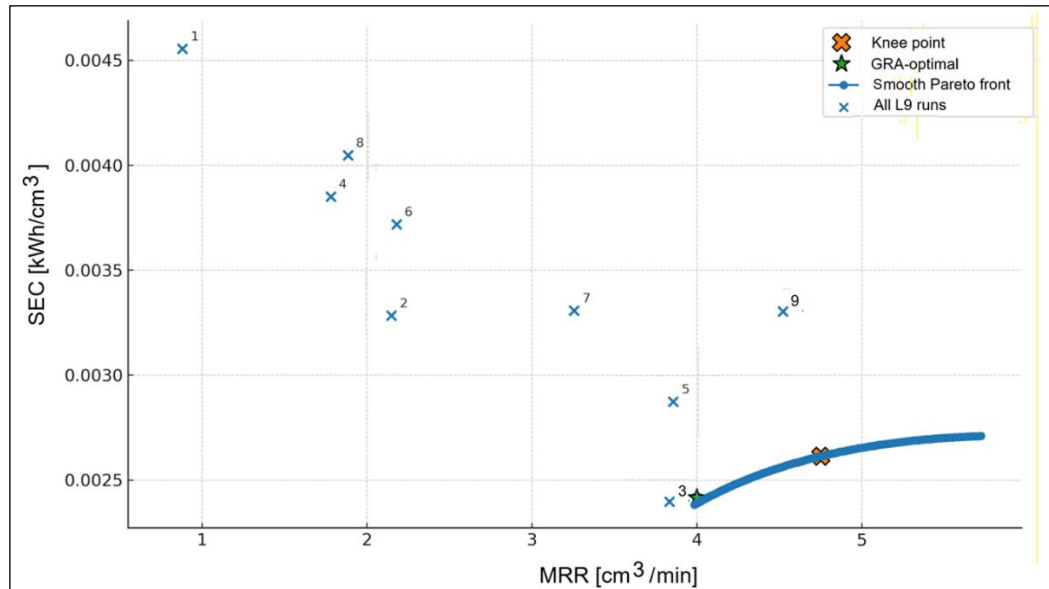


Figure 10: A comparison of the Pareto knee in the MRR–SEC plane with the GRA-selected solution.
Source: Authors, (2026).

V. CONCLUSIONS AND FUTURE WORK

- To improve dry turning of Inconel 625 in terms of specific energy consumption (SEC), material removal rate (MRR), surface roughness (R_a), and anticipated tool life (T_{pred}), an integrated Taguchi–GRA–Pareto/knee framework was created.
- ANOVA showed response-specific factor dominance: depth of cut is the dominant factor for both MRR and SEC, whereas feed rate mostly regulates surface roughness and tool-wear rate.
- The GRA-best solution was discovered to be inside the non-dominated region rather than on the Pareto front, despite the fact that Grey Relational Analysis (GRA) offered a scalar ranking of discrete cutting conditions.
- The robustness of the trade-off structure was confirmed by multi-objective optimization employing NSGA-II and ϵ -constraint, which consistently found the same MRR–SEC Pareto frontier [20–23].
- The results show that GRA and Pareto-based optimization are complementary, with knee-point selection offering actionable, energy-aware decision support beyond scalar rankings [21].
- Knee-point detection on the Pareto front produced a balanced operating condition that offers a justifiable compromise between productivity and energy efficiency.
- Expand the framework to incorporate environmental and economic factors (CO₂ emissions, tool cost).
- To improve statistical inference, include replicated experiments. • Use the technique for machining operations and other nickel-based superalloys.

VI. AUTHOR'S CONTRIBUTION

Conceptualization: Fitim Zeqiri and Fatlume Zhujani.

Methodology: Fatlume Zhujani.

Investigation: Fitim Zeqiri.

Discussion of results: Fitim Zeqiri and Fatlume Zhujani.

Writing – Original Draft: Fitim Zeqiri.

Writing – Review and Editing: Fatlume Zhujani.

Resources: Fitim Zeqiri.

Supervision: Fitim Zeqiri and Fatlume Zhujani.

Approval of the final text: Fitim Zeqiri and Fatlume Zhujani.

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