Optimization of atomized spray cutting fluid eco-friendly turning of Inconel 718 alloy using ARAS and CODAS methods

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Abstract
Atomized spray cutting fluid (ASCF) is a complex machining technology that results in increased productivity, improved surface quality, longer tool life, and cost savings. The purpose of this study is to investigate the effect of cutting process parameters on Inconel 718 alloy turning in dry and ASCF cutting environments. These two cooling environments’ essential machining indices, such as surface roughness, machining cost, power consumption, and tool life, were investigated. The cutting parameters were adjusted using desirability functional analysis, and two types of multicriteria decision-making (MCDM) methods were investigated: additive ratio assessment method (ARAS) and combinative distance-based assessment technique (CODAS). Both MCDM approaches yielded identical results, with the best settings being a cutting speed of 200 m/min, a feed rate of 0.08 mm/rev, and a depth of cut of 0.2 mm in an ASCF environment. ASCF machining considerably minimises the surface roughness, machining cost, power consumption and maximises the tool life by around 16%, 51%, 17%, and 48%, respectively, compared with dry machining.

Keywords Inconel 718 alloy · Turning · Desirability functional analysis · Multi-criteria decision-making (MCDM) · Surface roughness · Tool life · Machining cost · ARAS method · CODAS method

1 Introduction
Titanium and nickel-based superalloys are the most commonly utilised metallic materials in aircraft construction and mechanical components. Because of its great heat resistance qualities, this superalloy is widely employed. Inconel 718 alloys are classified as complicated materials that pose a challenge to the machining industry. Therefore, this high temperature/heat resistant material requires low-cost and high-performance machining techniques and processes [1]. Li et al. [2] investigated tool wear with two types of inserts: coated carbide inserts and ceramic inserts. The wear mechanism of these two cutting tools was found to be identical to that of abrasion, chipping, and adhesion, according to the study. A ceramic insert with a negative angle is preferable for machining Inconel 718 alloy. Gaitonde et al. [3] investigated the effect of various parameters on the performance of hard AISI-D2 steel utilising ceramic insert. They concluded that the depth of cut has a significant impact on tool wear and the development of uniform surface roughness in materials. Tool wear was investigated while turning an In-800 with a cubic boron nitride (cBN) insert to determine the best cutting conditions. The researchers also recommend coated
carbide tools and vegetable oil-assisted MQL solid additives [4] to prolong tool life and improve surface smoothness. Singh et al. [5] investigated the properties of cold air-assisted and biodegradable oil-based MQL during pure titanium machining. The authors concluded that the cold air-assisted MQL improved surface quality, reduced tool wear, and increased cutting forces. Many initiatives have been taken by researchers to boost production efficiency at a low cost. Many researchers used particular procedures (dry, MQL, cryogenic machining) to boost manufacturing efficiency at a reasonable cost. Nonetheless, most machining sectors have relied on cutting fluids to improve machining efficiency. When compared to flood cooling, minimum quantity lubrication (MQL) uses around one-third (50–100 mL/h) of the cutting fluid. The advantages of MQL in machining include increased tool life and a higher quality machined surface [6]. Few studies have been conducted to investigate the impact of atomized spray cutting fluid (ASCF) on titanium and nickel base alloy materials. The biggest challenge with machining Inconel 718 is producing a high cutting temperature in a work-tool contact that can react with the tool’s coating [7]. Increased cutting speed (v, 100 m/min) can cause increased cutting forces and temperature in the machine tool zone, reducing surface integrity and productivity [8].

The ASCF idea was created to increase tool life while decreasing coolant usage in Inconel 718 alloy machining. In the ASCF/MQL process, cutting fluid combined with water in various ratios (96:4–90:10) is usually utilised as the cutting fluid. The combinations are being utilised to reduce environmental effect. This method employs atomized thin droplets of cutting fluids (5–10 µm) that enter a machine environment. This method employs atomized thin droplets of cutting fluids (5–10 µm) that enter a machine environment. This method employs atomized thin droplets of cutting fluids (5–10 µm) that enter a machine environment. The International Journal of Advanced Manufacturing Technology (2022) 120:4551–4564

The SL-MQC technique performed to a study. Sartori et al. [14] conducted experiments on Ti-6Al-4 V with a little amount of liquid lubrication (MQL). Minimum quantity cooling (MQC) approach with multiple aqueous solutions containing varied percentages of graphite. The results showed that the SL-MQC technique performed the best in terms of tool wear and surface integrity. The goal of the machine tool industry is to improve production and efficiency, which is closely related to determining the optimum cutting parameters [15]. Unfortunately, determining the best combination of feed rate, depth of cut, and cutting speed can be difficult. This can improve surface smoothness, reduce tool wear, and increase overall productivity [15, 16].

The desirability function is a method for reducing complex multi-response features to a single response. Sait et al. [17] do a turning experiment on glass-fibre-reinforced plastic (GFRP) and use desirability function analysis to optimise process parameters (DSA). Similarly, optimal cutting parameters for turning EN25 steel with various coated carbide tools were chosen. The cutting speed of 244 m/min, feed rate of 0.10 mm/rev, and depth of cut of 1.0 mm with CVD-coated tool are an ideal parameter in the form of desirability functional analysis [18]. Swiercz et al. [19] used response surface methodology (RSM) and the desirability function to investigate the effect of machining parameters on material removal rate (MRR), surface roughness (Ra), and white layer thickness (WL) during electrical discharge machining (EDM) (DF). The discharge current and time had the greatest impact on the MRR, Ra, and WL. Vijay Kumar Sharma et al. [20] used Taguchi-based DF to study the machinability of EN 31 steel under dry, MQL, and flood cooling. Under flood cooling, the greatest composite desirability (CD) value of 0.9879 was observed at a cutting speed of 110 m/min, feed rate of 60 mm/min, and depth of cut of 0.4 mm.

Several researchers have used the multicriteria decision-making (MCDM) tool in a variety of industries, including manufacturing, thermal, supplier selection, finance, and solar application [21]. Singaravel et al. [22] used the additive ratio assessment (ARAS) technique to establish the best process variables (cutting speed, feed rate, and depth of cut) and coated tools for turning the operation with AISI 4340 steel. They proposed 161 m/min cutting speed, 0.24 mm/rev feed rate, and 1.2 mm depth of cut through CVD-coated tool as the optimal combination of cutting parameters for quick decrease of surface roughness, microhardness, and maximisation of material removal rate (MRR). Ghenai et al. [23] used the ARAS and step-wise weight assessment ratio technique to optimise the sustainability indicators for renewable energy (RE) systems such as solar photovoltaic, wind energy, phosphoric acid fuel cell, and solid oxide fuel cell. This research identified five distinct sustainability criteria for various industries: resource, environment, social, economic, and technological. The criteria were then applied to the various subcategories of energy construction. Land-based wind
energy systems are ranked highest in terms of sustainability pointers and sub-points, followed by solid oxide and then phosphoric acid fuel cells, with polycrystalline solar energy systems rated worst. Using the ARAS approach, Marichamy et al. [24] discovered the best process parameters and suited for the welding operation of A319 aluminum alloy. For connecting the component, the ideal joining consideration welding feed is 40 mm/min, the rotation speed is 700 rpm, and the tool pin diameter is 6 mm. Kumar et al. [25] used ARAS, grey relational analysis, and the Taguchi method to improve the machinability of the AA7050-T6 % B4C composite using die sinking EDM. They discovered that the ARAS technique has the lowest percentage error when compared to grey relational analysis. As a result, the ARAS approach is now a viable tool for improving EDM process parameters.

Ramezanali et al. [26] proposed a decision-making methodology based on the Best–Worst and ARAS methodologies for assigning weightage to spatial proxies in ore-forming minerals processing. The findings of this technique were compared with those of TOPSIS and index-overlay in the investigation region, highlighting the superiority of the ARAS technique. Using the ARAS technique, Goswami et al. [27] chose the best alternative material for engineering applications from among seven options based on six sub-criteria (bending fatigue limit, core hardness, cost, surface hardness, ultimate tensile strength, and surface fatigue limit). According to their findings, cast alloy steel is the best choice, followed by cast iron and carburized steels, while hardened alloy steel is the worst choice within the group. Balki et al. [28] investigated engine operating variables with a tiny SI engine and alternative fuels utilising the SWARA and ARAS hybrid approach. Based on the results, the best working characteristics for pure methanol fuel were 9.0:1 compression ratio, 1.1 air surplus coefficient, and crankshaft angle of 20° ignition timing. According to Çolak et al. [29], energy storage alternatives are crucial and can be accurately measured as an MCDM problem. They assessed the difficulty in terms of both quantitative and qualitative factors. They discovered that the energy storage technology (EST) option known as “Compressed Air” was the best acceptable energy storage technology solution for Turkey. Radović et al. [30] used the ARAS approach to investigate performance measurement in transportation enterprises based on 20 performance metrics. Their findings show that transportation companies in Serbia, Bosnia and Herzegovina, and Croatia outperform transportation companies in Libya. Keshavarz Ghorabae et al. [31] developed a fuzzy version of the CODAS technique for market segment evaluation and selection. The results show that the fuzzy CODAS technique is more successful and dependable than the other approaches, and the sensitivity analysis demonstrates the consistency of the suggested technique’s conclusions. Karaşan et al. [32] proposed a new CODAS technique for identifying wind energy facility locations. According to the sensitivity analysis, the specific output for the wind plant location is relatively resilient. CODAS approaches have been widely employed by researchers in a variety of applications, including supplier selection [33], energy storage [34], machine tool selection [35], material selection [36, 37], site selection [38], and market segment [31].

Based on a desirability method, ARAS, and CODAS MCDM, this work proposes to find, assess, and optimise turning process parameters for attaining a high-quality response for Inconel 718 alloy. The L18 Taguchi orthogonal array (OA) experiment is conducted to determine the best process parameters for surface roughness, machining cost, power consumption, and tool life. Based on the preceding research, the current work proposes an integrated MCDM technique for selecting the appropriate turning parameters. As a result, our research contributes significantly to bridging the aforementioned gap.

2 Materials and methods

The workpiece was made of Inconel 718 alloy with dimensions of 80×400 mm. Tensile strength (1170 MPa), yield strength (1375 MPa), elongation (23.3%), and hardness (40 HRC). Chemical composition (% weight) – Ni (53), Cr (18), C (0.04), Mn (0.08), Si (0.08), Co (0.23), Mo (3.04), Nb (5.3), Ti (0.98), Al (0.50), Fe (17.80). For turning trials, a CNC DAEWOO PUMA-2000 machine (China) was employed. As a tool holder for machining, ceramic inserts with SNGA 120412 T T01-WG 300 grade (Al2O3 + SiC whiskers) and MSDNN 2525 M12–Greenleaf Corporation, USA are utilised. The ASCF method is used in this study to investigate the influence of cutting fluid with solid lubricants on tool wear. Dry machining is also utilised to demonstrate the superiority of the ASCF process. The ASCF method employed two types of solid lubricants: graphite and molybdenum disulfide (MoS2).

To ensure homogenous particle dispersion, 0.2 weight percent of each solid lubricant is mixed with acetone in 20 mL. Following that, cutting fluid was combined with solid lubricant in a 90:10 ratio. The flow adjustable valve engages the coolant flow rate of 30 mL/h at a pressure of 7 bar. The nozzle-to-tool tip distance is set to 50 mm, and the length of cut (Loc) is set to 40 mm. The turning experiments were conducted with cutting speeds (vc) of 100, 150, and 200 m/ min, feed rates (f) of 0.04, 0.08, and 0.12 mm/rev, and cutting depths (ap) of 0.2, 0.4, and 0.6 mm in dry and ASCF cutting environments, as indicated in Table 1. To correctly examine machining performance, a new cutting insert is used for each experiment. The workpiece’s surface roughness was assessed using a contact-type surface roughness tester (TR200) (Ra). For the machined surface, a Keyence...
VH-Z500R optical light microscope with a magnification range of (500–×5000) was employed. The schematic diagram for the dry and ASCF procedures is shown in Fig. 1. Table 2 depicts the design of the L18 orthogonal array experimental study.

### 3 Optimisation

#### 3.1 Desirability function analysis

The concept of the desirability function was proposed by Harrington [39]. The desirability approach combines the functions [0, 1] to create a standard scale metric. It works by transforming each estimated response \( y_i \) into a unitless utility bounded by \( 0 < d_i < 1 \) [40] (Fig. 2).

(i) **Larger the better**

The value of \( y_i \) is expected to be smaller than the desirable value \( d_i = 1 \). \( y_i < y_{	ext{min}} \) \( (d_i = 0) \) undesirable value. \( d_i \) values lie in the range of [0 1] are shown in Eq. (1).

\[
d_i = \begin{cases} 0 & \text{if } y_i < y_{	ext{min}} \\ \left( \frac{y_i - y_{	ext{min}}}{y_{	ext{max}} - y_{	ext{min}}} \right)^s & \text{if } y_{	ext{min}} \leq y_i \leq y_{	ext{max}}, s \geq 0 \\ & \text{if } y_i > y_{	ext{max}} \\ \end{cases}
\]

(ii) **Smaller the better**

The value of \( y_i \) is expected to be larger than the desirable value \( d_i = 1 \). \( y_i > y_{	ext{max}} \) \( (d_i = 0) \) undesirable value. \( d_i \) values lie in the range of [0 1] are shown in Eq. (2).

\[
d_i = \begin{cases} 0 & \text{if } y_i > y_{	ext{max}} \\ \left( \frac{y_{	ext{max}} - y_i}{y_{	ext{max}} - y_{	ext{min}}} \right)^r & \text{if } y_{	ext{min}} \leq y_i \leq y_{	ext{max}}, r \geq 0 \\ & \text{if } y_i < y_{	ext{min}} \\ \end{cases}
\]

Composite desirability \( (CD) \) is presented in Eq. (3). \( d_1, d_2, d_3 \) are the individual desirable index. \( w_1, w_2, w_3 \) ..... weightage value.

\[
CD = \left( d_1^{w_1} \times d_2^{w_2} \times d_3^{w_3} \times \ldots \right)^{1/k}
\]

#### 3.2 Entropy method

The Shannon entropy is a method that calculates the weights of decision criteria after taking the initial decision matrix [41].

Step 1: Project outcome \( (P_{ij}) \) is obtained by normalising the arrays of a decision matrix.

\[
P_{ij} = \frac{x_{ij}}{\sum_{i=1}^{m} x_{ij}}
\]

Step 2: Calculation of the entropy measure of project outcomes
Step 3: Defining the objective weight based on the entropy concept

\[ E_j = -k \sum_{j=1}^{m} P_{ij} \times \ln P_{ij}, \quad \left( k = \frac{1}{\ln(m)} \right) \] (5)

\[ W_j = \frac{1 - E_j}{\sum_{j=1}^{n} (1 - E_j)} \] (6)

Step 3: Defining the objective weight based on the entropy concept

\[ W_j = \frac{1 - E_j}{\sum_{j=1}^{n} (1 - E_j)} \]

3.3 Additive ratio assessment method

The additive ratio assessment (ARAS) is a conceptual evaluation system developed by Zavadskas and Turskis in 2010 [42]. ARAS is a conceptual model that compares the performance of various alternatives to the ideal alternative [43]. This method is used in various fields of study.

Step 1: Forming of decision—making matrix (DMM)

\[ X = \begin{bmatrix} x_{01} & x_{02} & \cdots & x_{0n} \\ x_{11} & x_{12} & \cdots & x_{1n} \\ \vdots & \vdots & \ddots & \vdots \\ x_{m1} & x_{m2} & \cdots & x_{mn} \end{bmatrix} \] (7)

\[ S_j = \frac{\sum_{j=1}^{n} \hat{w}_j}{\sum_{j=1}^{n}} \] (11)

Table 2 L18 orthogonal array

| S no | Coded value | Surface Roughness (SR) | Tool life (TL) | Machining cost (MC) | Power consumption (PC) |
|------|-------------|------------------------|---------------|---------------------|-----------------------|
| A    | B           | C                      | D             |                     |                       |
| 1    | 1           | 1                      | 1             | 1                   | 0.478                 |
| 2    | 1           | 2                      | 2             | 1                   | 0.524                 |
| 3    | 1           | 3                      | 3             | 1                   | 0.755                 |
| 4    | 2           | 1                      | 1             | 1                   | 0.642                 |
| 5    | 2           | 2                      | 1             | 1                   | 0.71                  |
| 6    | 2           | 3                      | 1             | 1                   | 0.684                 |
| 7    | 3           | 1                      | 1             | 2                   | 0.772                 |
| 8    | 3           | 2                      | 2             | 1                   | 0.657                 |
| 9    | 3           | 3                      | 1             | 1                   | 0.71                  |
| 10   | 1           | 1                      | 3             | 1                   | 0.444                 |
| 11   | 1           | 2                      | 1             | 2                   | 0.409                 |
| 12   | 1           | 3                      | 2             | 2                   | 0.523                 |
| 13   | 2           | 1                      | 1             | 2                   | 0.456                 |
| 14   | 2           | 2                      | 3             | 2                   | 0.585                 |
| 15   | 2           | 3                      | 1             | 2                   | 0.476                 |
| 16   | 3           | 1                      | 3             | 2                   | 0.576                 |
| 17   | 3           | 2                      | 1             | 2                   | 0.476                 |
| 18   | 3           | 3                      | 2             | 2                   | 0.572                 |

\[ x_{ij} = \begin{cases} \text{Max } x_{ij} & \text{if } j \in \text{Beneficial} \\ \text{Min } x_{ij} & \text{if } j \in \text{NonBeneficial} \end{cases} \] (8)

Step 2: Normalization of decision matrix

\[ \tilde{x}_{ij} = \frac{x_{ij}}{\sum_{i=0}^{m} x_{ij}}, \quad \bar{x}_{ij} = \frac{x_{ij}}{\sum_{j=1}^{n} x_{ij}} \] (9)

Step 3: Weighted normalized decision matrix

\[ \hat{x}_{ij} = \hat{w}_j x_{ij}, \quad i = 0, \ldots, m, \quad \sum_{j=1}^{n} \hat{w}_j = 1 \] (10)

\[ \hat{X} = \begin{bmatrix} \hat{x}_{01} & \hat{x}_{02} & \cdots & \hat{x}_{0n} \\ \hat{x}_{11} & \hat{x}_{12} & \cdots & \hat{x}_{1n} \\ \vdots & \vdots & \ddots & \vdots \\ \hat{x}_{m1} & \hat{x}_{m2} & \cdots & \hat{x}_{mn} \end{bmatrix}, (i = 0, 1, \ldots, m; j = 1, 2, \ldots, n) \] (10)
Fig. 2 Schematic flow chart of MCDM methods
Step 5: Determine the degree of utility $K_i$ for each of the alternatives

$$K_i = \frac{S_i}{S_o}; \quad i = 0, ..., m$$

(12)

3.4 Combinative distance-based assessment method

A new type of decision-making method known as combinatorial distance-based assessment (CODAS) is proposed to consider problems with multicriteria decisions. The method is formulated by taking into account the Euclidean distance of alternatives from the negative [31].

Step 1: Developing the initial decision matrix

$$X = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1m} \\ x_{21} & x_{22} & \cdots & x_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ x_{n1} & x_{n2} & \cdots & x_{nm} \end{bmatrix}$$

(13)

Step 2: Normalise decision matrix

$$n_{ij} = \begin{cases} \frac{x_{ij}}{\max_{j} x_{ij}} & \text{if } j \in \text{Beneficial} \\ \frac{x_{ij}}{\min_{j} x_{ij}} & \text{if } j \in \text{NonBeneficial} \end{cases}$$

(14)

Step 3: Weighted normalize decision matrix

$$r_{ij} = w_i n_{ij}$$

(15)

Step 4: Determine the negative ideal solution points

$$ns = \begin{bmatrix} ns_1 \\ \vdots \\ ns_m \end{bmatrix}$$, \(ns_i = \min r_{ij}\)

(16)

Step 5: Calculate the Euclidean and Taxicab distances of alternatives from the negative ideal solution

$$E_i = \sqrt{\sum_{j=1}^{m} (r_{ij} - ns_j)^2}, \quad T_i = \sum_{j=1}^{m} |r_{ij} - ns_j|$$

(17)

Step 6: Construct the relative assessment matrix

$$Ra = \begin{bmatrix} h_{ik} \\ \vdots \\ h_{im} \end{bmatrix}, \quad h_{ik} = (E_i - E_k) + (\psi(E_i - E_k)X(T_i - T_k))$$

(Assume, $\psi = 0.02$)

(18)

Step 7: Calculate the assessment score and rank alternatives

$$H_i = \sum_{k=1}^{n} h_{ik}$$

(19)

4 Results and discussion

4.1 Estimated desirability values

This study aims to determine “smaller the better” and “larger the better” characteristics of individual desirability values

| Table 3 Estimated desirability values |
|-----------------------------|-----------------|-----------------|-----------------|
| Exp no | SR (µm) | MC ($/cm^3$) | PC (kW) | TL (min) | Individual desirability | Composite desirability (CD) | Rank |
|-------|--------|-------------|------|-----|------------------|-----------------|-----|
|       |        |             |      |     | SR     | MC     | PC     | TL     | SR     | MC     | PC     | TL     |                |       |
| 1     | 0.478  | 4.3         | 0.403| 11.2| 0.810  | 0.000  | 0.950  | 0.423  | 0.000  | 0.750  | 0.797  | 0.683  | 0.874  | 0.950  | 0.310  | 15 |
| 2     | 0.524  | 1.29        | 0.69 | 8.7  | 0.683  | 0.754  | 0.802  | 0.263  | 0.574  | 0.103  | 0.157  | 0.165  | 0.185  | 0.103  | 0.157 | 10 |
| 3     | 0.755  | 0.773       | 1.16 | 6.2  | 0.047  | 0.884  | 0.561  | 0.103  | 0.221  | 0.129  | 0.157  | 0.165  | 0.185  | 0.103  | 0.157 | 14 |
| 4     | 0.642  | 1.42        | 1.513| 6.4  | 0.358  | 0.721  | 0.379  | 0.115  | 0.326  | 0.129  | 0.157  | 0.165  | 0.185  | 0.103  | 0.157 | 12 |
| 5     | 0.71   | 1.76        | 0.657| 8.4  | 0.171  | 0.636  | 0.819  | 0.244  | 0.384  | 0.129  | 0.157  | 0.165  | 0.185  | 0.103  | 0.157 | 11 |
| 6     | 0.684  | 0.762       | 2.25 | 5.9  | 0.242  | 0.886  | 0.000  | 0.083  | 0.000  | 0.129  | 0.157  | 0.165  | 0.185  | 0.103  | 0.157 | 15 |
| 7     | 0.772  | 1.67        | 1.89 | 6.15 | 0.000  | 0.659  | 0.185  | 0.099  | 0.000  | 0.129  | 0.157  | 0.165  | 0.185  | 0.103  | 0.157 | 15 |
| 8     | 0.657  | 0.631       | 1.93 | 5.8  | 0.317  | 0.919  | 0.165  | 0.077  | 0.246  | 0.129  | 0.157  | 0.165  | 0.185  | 0.103  | 0.157 | 13 |
| 9     | 0.71   | 1.517       | 2.1  | 4.6  | 0.171  | 0.697  | 0.077  | 0.000  | 0.000  | 0.129  | 0.157  | 0.165  | 0.185  | 0.103  | 0.157 | 15 |
| 10    | 0.444  | 3.05        | 0.306| 20.2 | 0.904  | 0.313  | 1.000  | 1.000  | 0.729  | 0.129  | 0.157  | 0.165  | 0.185  | 0.103  | 0.157 | 4  |
| 11    | 0.049  | 0.809       | 0.478| 19.37| 1.000  | 0.874  | 0.912  | 0.947  | 0.932  | 1      |
| 12    | 0.523  | 0.399       | 0.923| 15.32| 0.686  | 0.977  | 0.683  | 0.687  | 0.749  | 3      |
| 13    | 0.456  | 0.827       | 1.417| 14.2 | 0.871  | 0.870  | 0.428  | 0.615  | 0.668  | 8      |
| 14    | 0.585  | 1.762       | 0.635| 17.2 | 0.515  | 0.636  | 0.831  | 0.808  | 0.685  | 7      |
| 15    | 0.476  | 0.326       | 1.39 | 15.21| 0.815  | 0.995  | 0.442  | 0.680  | 0.703  | 6      |
| 16    | 0.576  | 0.853       | 0.788| 16   | 0.540  | 0.863  | 0.752  | 0.731  | 0.711  | 5      |
| 17    | 0.476  | 0.308       | 0.762| 14   | 0.815  | 1.000  | 0.765  | 0.603  | 0.783  | 2      |
| 18    | 0.572  | 0.616       | 1.338| 12   | 0.551  | 0.923  | 0.469  | 0.474  | 0.580  | 9      |
to minimize surface roughness, machining cost, and power consumption and maximise the tool life. Individual desirability of \( d_{SR} \), \( d_{MC} \), and \( d_{PC} \) are calculated by Eq. (1). Larger the better desirability of \( d_{TL} \) is calculated by Eq. (2). The \( CD_i \) values are computed using Eq. 3. The equal weightage of 0.25 is considered for all parameters as shown in Table 3. The highest \( CD_i \) values obtained 0.932 and the corresponding \( d_{SR} \), \( d_{MC} \), \( d_{PC} \), and \( d_{TL} \) are 1, 0.874, 0.912, and 0.947 respectively.

\[
d_{SR} = \left\{ \begin{array}{ll}
\frac{1}{r} \left( \frac{y_i - 0.772}{0.409 - 0.772} \right)^r, & y_i < 0.409 \\
0.409 \leq y_i \leq 0.772, & r \geq 0 \\
y_i > 0.772
\end{array} \right.
\]

(20)

\[
d_{MC} = \left\{ \begin{array}{ll}
\frac{1}{r} \left( \frac{y_i - 4.3}{0.308 - 4.3} \right)^r, & y_i < 0.308 \\
0.308 \leq y_i \leq 4.3, & r \geq 0 \\
y_i > 4.3
\end{array} \right.
\]

(21)

\[
d_{PC} = \left\{ \begin{array}{ll}
\frac{1}{r} \left( \frac{y_i - 2.25}{0.306 - 2.25} \right)^r, & y_i < 0.306 \\
0.306 \leq y_i \leq 2.25, & r \geq 0 \\
y_i > 2.25
\end{array} \right.
\]

(22)

\[
d_{TL} = \left\{ \begin{array}{ll}
\frac{1}{r} \left( \frac{y_i - 4.6}{20.2 - 4.6} \right)^r, & 4.6 \leq y_i \leq 20.2, s \geq 0 \\
y_i > 20.2
\end{array} \right.
\]

(23)

\[
CD_i = (0.810 \times 0.000 \times 0.950 \times 0.423)^{\frac{1}{4}}
\]

(24)

The mean composite desirability factor \( CD \) is shown in Fig. 3. The response factor at each level on \( CD \) is presented in Table 4. The highest \( CD \) is achieved at levels 2, 1, 2, and 2 for environmental factors, cutting speed, feed rate, and depth of cut, respectively. The optimum parameters for the \( SR \), \( MC \), \( PC \), and \( TL \) are \( A_2B_1C_2D_2 \), i.e. environment (ASCF), cutting speed of 100 m/min, feed rate of 0.8 mm/rev, and depth of cut of 0.4 mm.

The conformation experiment was conducted with optimal parameters. The initial parameter setting at 11th experiment as ASCF environment, cutting speed of 100 m/min, feed rate of 0.08 mm/rev, and depth of cut 0.2 mm is \( A_2B_1C_2D_1 \), and the corresponding \( CD \) value is 0.931, as shown in Table 4. An improved \( CD \) at the optimum parameter setting \( A_2B_1C_2D_2 \) is achieved by optimizing the \( SR \), \( MC \),

![Main Effects Plot for Composite Desirability](image)

**Table 4** Response table for means

| Factors       | Mean composite desirability | Factor effect | Rank |
|---------------|-----------------------------|---------------|------|
|               | Levels                      |               |      |
| Environment   | 1  | 2  | 3  |               |      |
| Cutting speed | A  | 0.1946 | **0.7268** | --  | 0.5322 | 1    |
| Feed rate     | B  | 0.5342 | 0.4610   | 0.3868 | 0.1474 | 3    |
| Depth of cut  | C  | 0.4059 | **0.6007** | 0.3754 | 0.2252 | 2    |
|               | D  | 0.4574 | **0.4925** | 0.4321 | 0.0604 | 4    |

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PC, and TL configurations through desirability functional analysis. SR decreased from 0.409 to 0.378 µm, MC reduced from 0.809 to 0.765 ($/cm^3), PC decreased from 0.478 to 0.452 kW, and TL improved from 19.37 to 20.1 min. The percentage improvement observed in SR, MC, PC, TL, and CD is noted as 8.2, 5.75, 5.75, 6.43, and 6.34, respectively, as shown in Table 5.

Furthermore, desirability function analysis is compared with well known MCDM techniques such as ARAS and CODAS method, in order to compare the optimal setting parameter with DFA and MCDM techniques. The turning process parameters like SR, TL, MC, and PC are optimized with ARAS using the experimental values. First, the individual weightage of each response is calculated by the entropy method from Eqs. 4–6. Entropy weights for SR, TL, MC, and PC are 0.037, 0.193, 0.496, and 0.274 respectively. The normalized decision matrix and weightage normalized decision are obtained from Eqs. 7–10. ARAS defines the optimal performance measure as the relative closeness of the optimality function to the measure’s highest rank. The function’s closeness as the most appropriate value for the evaluation is presented in Eqs. 11–12. Experiment number 17 has the highest degree of utility value (0.777), as can be observed from the results as shown in Table 6.

CODAS method is used to determine the desirability of alternatives. The two measures are related to the Euclidean distance of alternatives from the negative-ideal. The CODAS measures the performance of an alternative by looking at the distances between the taxicab and the Euclidean distance. If the distance is very close to each other, the CODAS uses the Taxicab distance as the primary measure of comparison. The normalized and weightage normalized performance values are computed for each of the criteria using Eqs. 13–15. Then, Eq. 16 calculates the negative-ideal solution. From the negative ideal solution, two alternatives, taxicab and the Euclidean distance also computed, are presented in Eq. 17. The relative assessment matrix and the assessment scores of alternatives can be calculated using Eqs. 18–19, as shown in Table 7. Table 7 shows that experiment no. 17 has the

### Table 5 Response table for means

| Experimental Value | Initial settings | Optimum setting | % Improvement |
|--------------------|------------------|-----------------|---------------|
|                    | A_2B_1C_2D_1    | A_2B_1C_2D_2   |               |
| SR (µm)            | 0.409           | 0.378           | 8.20          |
| MC ($/cm^3)        | 0.809           | 0.765           | 5.75          |
| PC (kW)            | 0.478           | 0.452           | 5.75          |
| TL (min)           | 19.37           | 20.1            | 6.43          |
| CD_i               | 0.931           | 0.994           | 6.34          |

### Table 6 ARAS method optimality function and degree of utility preference with rank values

| Optimum value | Normalize decision matrix | Weighted normalized decision matrix | Optimality function ($S_i$) | Degree of utility ($K_i$) | Rank |
|---------------|---------------------------|----------------------------------|-----------------------------|---------------------------|------|
| SR (µm)      | 0.060 0.009 0.099 0.049   | 0.002 0.004 0.027 0.009 0.043 | 0.368                       | 10                        |
| MC ($/cm^3)  | 0.055 0.029 0.058 0.038   | 0.002 0.014 0.015 0.007 0.040 | 0.341                       | 13                        |
| PC (kW)      | 0.038 0.049 0.034 0.027   | 0.001 0.024 0.009 0.005 0.040 | 0.347                       | 12                        |
| TL (min)     | 0.045 0.027 0.026 0.028   | 0.001 0.013 0.007 0.005 0.027 | 0.236                       | 16                        |
| CD_i         | 0.040 0.021 0.060 0.037   | 0.001 0.010 0.016 0.007 0.036 | 0.307                       | 15                        |
| SR (µm)      | 0.042 0.050 0.017 0.026   | 0.001 0.025 0.004 0.005 0.036 | 0.310                       | 14                        |
| MC ($/cm^3)  | 0.037 0.023 0.021 0.027   | 0.001 0.011 0.005 0.005 0.023 | 0.202                       | 17                        |
| PC (kW)      | 0.044 0.061 0.020 0.025   | 0.001 0.030 0.005 0.004 0.042 | 0.361                       | 11                        |
| TL (min)     | 0.040 0.025 0.019 0.020   | 0.001 0.012 0.005 0.003 0.023 | 0.197                       | 18                        |
| CD_i         | 0.065 0.012 0.130 0.089   | 0.002 0.006 0.035 0.017 0.061 | 0.523                       | 5                         |
| SR (µm)      | 0.070 0.047 0.083 0.085   | 0.002 0.023 0.022 0.016 0.065 | 0.557                       | 4                         |
| MC ($/cm^3)  | 0.055 0.096 0.043 0.067   | 0.002 0.048 0.011 0.013 0.074 | 0.636                       | 3                         |
| PC (kW)      | 0.063 0.046 0.028 0.062   | 0.002 0.023 0.007 0.012 0.045 | 0.384                       | 8                         |
| TL (min)     | 0.049 0.021 0.063 0.075   | 0.001 0.010 0.017 0.014 0.044 | 0.378                       | 9                         |
| CD_i         | 0.060 0.118 0.028 0.067   | 0.002 0.058 0.007 0.012 0.081 | 0.694                       | 2                         |
| SR (µm)      | 0.050 0.045 0.050 0.070   | 0.001 0.022 0.013 0.013 0.051 | 0.439                       | 6                         |
| MC ($/cm^3)  | 0.060 0.125 0.052 0.061   | 0.002 0.062 0.014 0.011 0.090 | 0.770                       | 1                         |
| PC (kW)      | 0.050 0.062 0.029 0.052   | 0.001 0.031 0.008 0.010 0.051 | 0.435                       | 7                         |
highest relative assessment matrix \((H)\) value of 6.971. As a result, in CODAS method evaluation, experiment number 17 is the optimum process parameter.

In both MCDM techniques, experiment number 17 is the optimal parameter setting for as ASCF environment, cutting speed of 200 m/min, feed rate of 0.08 mm/rev, and depth of cut 0.2 mm is \((A_2B_2C_2D_2)\) and the corresponding SR, TL, MC, and PC are 0.476, 14, 0.496, and 0.274 respectively. There is a variation in the optimal parameter setting in DFA over MCDM techniques; this is due to complexity in the

Fig. 4 Rank values of a different experiment
mathematical formulation such as entropy weightage, degree of utility, and relative assessment matrix. The cutting speed of 200 m/min and depth of cut 0.2 mm are the two factors significantly changed in MCDM techniques; other responses feed rate 0.08 mm/rev and ASCF machining environment are similar. The same parameter setting ($A_1B_2C_2D_1$) is conducted in dry environment, and the corresponding $SR$, $TL$, $MC$, and $PC$ are 0.572, 7.2, 0.631, and 0.923 respectively.

Figure 4 displays the degree of utility and relative assessment values of Inconel 718 alloy using an ARS and CODAS technique, respectively. It can be noticed from the figure that the 17th experiment is the best experimental condition for both optimization methods, such as ARS and CODAS, due to its higher cutting speed of 200 m/min, feed rate of 0.08 mm/rev, and low depth of cut of 0.2 mm under ASCF environment condition compared with the other experimental conditions. The ARS and CODAS have the highest degree of utility and relative assessment values of 0.7701 and 6.9706, respectively. It can be noticed from Tables 6 and 7 that the worst experimental condition for ADAS was the 9th experimental condition and CODAS was the 7th experimental condition. The ARS and CODAS have the lowest degree of utility and relative assessment values of 0.1974 and $-2.6643$, respectively.

The surface defects of dry and ASCF machining at optimum parameters cutting speed of 200 m/min, feed rate of
0.08 mm/rev, depth of cut of 0.2 mm as shown in Fig. 5. The scratches and feed marks produced by dry machining are higher than those produced by the atomized spray cutting fluid. This is due to a fine droplet of solid additive lubricant, and vegetable oil improves heat absorption at the machining zone. In addition, fine spray droplets reduce the friction between the tool tip and the workpiece surface. This ensures that the sharpness of the tool tip stays at an elevated temperature [44, 45]. The generation of an adhesive film at the cutting speed of 200 m/min on the rake face during the turning of an Inconel alloy has been observed. This phenomenon is caused by the high stresses and strain hardening that the alloy undergoes during the machining. Also, the use of spray coolants helps in preventing the formation of abrasion and another diffusion during dry machining. Solid lubricant helps to minimize the amount of heat absorbed by the tool and significantly improve the tool life [46–49]. ASCF particles can help reduce friction between the tool and the workpiece by forming a protective film layer. The conclusion is likewise consistent with those of An et al. [50] and Pal et al. [51]. As illustrated in Figs. 5 and 6, the ASCF condition produces the best surface quality and the least tool wear.

5 Conclusions

This research provides an in-depth examination of the dry and atomized spray cutting fluid (ASCF) lubrication methods used to convert Inconel 718 alloy using composite desirability function analysis, ARS, and CODAS methods.

1. The composite desirability index (CD) of the optimum parameter setting (A2B1C2D2) is 6.34% higher than the original parameter setting (A2B1C2D1). The CD value of the best parameter settings ranges from 0.994 to A2B1C2D2. The ARAS and CODAS MCDM models discovered that experiment number 17 is rated first, followed by experiment number 7, and experiment number 9 is ranked last.

2. The ideal process parameters in both MCDM approaches were cutting speed of 200 m/min, feed rate of 0.08 mm/rev, depth of cut of 0.2 mm, and ASCF environment; the machining output response surface roughness of 0.476 m, machining cost 0.308$/cm3, power consumption 0.762 kW, and tool life 14 min. Because of its cooling and lubricating effect, fine droplets of ASCF machining are more efficient in lowering surface roughness values.

3. When compared to dry machining, ASCF machining considerably reduces surface roughness, machining cost, and power consumption while increasing tool life by about 16%, 51%, 17%, and 48%, respectively. Because of its good heat dissipation in the cutting zone, ASCF machining reduces power consumption figures. They lower the cutting forces, requiring less power to pry the chips from its resistant body.

4. Under dry conditions, the abrasion and adhesion mechanisms were seen, but ASCF machining resulted in less wear. The reason for this is that small droplets of ASCF increase the thermal conductivity of cutting fluids, allowing more heat to be transported from the cutting zone.

More research on the effects of various machining factors on quality responses could be done. For example, the impact of varying weight percentages of solid lubricant additives on the machining process could be investigated.

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Declarations

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