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A Novel Assessment Model for the Sustainability of Clean Cutting Technology Based on Game Theory

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Abstract

To enhance the sustainability of manufacturing, various clean cutting technologies have been developed, yet their sustainability assessment faces challenges in balancing multiple conflicting objectives and stakeholder interests. This paper proposes a game theory-based evaluation framework that treats environmental, technical, economic, and social dimensions as cooperative players. The Nash equilibrium model is employed to dynamically reconcile subjective weights from the analytic hierarchy process and objective weights from the entropy method, thus achieving optimal weight allocation. Experimental studies on Ti-6Al-4V titanium alloy milling compared dry milling, minimum quantity lubrication, and cryogenic minimum quantity lubrication (CMQL) under different parameters. Results demonstrate that the game-theoretic model effectively integrates preferences and achieves Nash equilibrium. CMQL showed superior performance, increasing tool life by approximately 40% and reducing surface roughness by about 25% compared to dry milling. Coated inserts reduced carbon emissions by nearly 30% versus end mills. The Nash equilibrium analysis demonstrates that dry milling with coated inserts attains the highest level of processing sustainability under high-speed conditions due to synergistic environmental and economic advantages, while simultaneously revealing practical trade-offs among competing objectives. This study confirms that the proposed framework enables scientific weight coordination and provides a quantifiable, interpretable decision-making system for sustainable process selection.

Keywords: sustainability assessment; decision-support framework; analytic hierarchy process; entropy weight method; game theory

1. Introduction

Manufacturing, as a cornerstone of global economic development and social advancement, has generated substantial material wealth while simultaneously confronting severe challenges such as excessive resource consumption, energy-intensive emissions, and ecological degradation. In response, the United Nations Environment Programme (UNEP) promotes a green economy paradigm that emphasizes the systematic reduction of environmental risks and resource dependence while enhancing social welfare and equity throughout economic growth [1]. Against this backdrop, clean cutting technology has emerged as a pivotal research frontier in advanced manufacturing due to its potential to reconcile processing efficiency with environmental sustainability.

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Clean cutting technologies aim to achieve a synergistic enhancement of machining performance and environmental sustainability through the optimization of cooling and lubrication strategies. Among the current approaches—dry cutting, minimum quantity lubrication (MQL), and cryogenic minimum quantity lubrication (CMQL)—each exhibits distinct characteristics, making them suitable for specific production contexts with unique advantages and limitations. Dry cutting eliminates the use of cutting fluids entirely, offering significant benefits in minimizing waste liquid generation and reducing coolant-related operational costs [2]. However, due to the absence of effective thermal management and lubrication, DRY often results in accelerated tool wear and degraded surface integrity, particularly when machining difficult-to-cut materials. MQL addresses these challenges by delivering a precisely metered amount of lubricant directly to the cutting zone, thereby improving surface finish and moderating cutting temperatures. For instance, Karim et al. [3] demonstrated substantial improvements in surface roughness and reduced thermal loads during aluminum alloy milling using MQL; Khan et al. [4] further showed that MQL surpasses conventional flood cooling in both energy efficiency and economic viability. Nevertheless, MQL's cooling capacity remains inadequate under high-thermal-load conditions. To address this limitation, CMQL integrates low-temperature cooling with micro-lubrication, demonstrating strong potential in suppressing tool wear and enhancing chip control. Cheng et al. [5] confirmed that CMQL significantly extends tool life by delaying wear progression, while Cai et al. [6] highlighted the superior comprehensive performance of supercritical carbon dioxide-based composite lubrication systems in titanium alloy machining. Further supporting evidence comes from studies on alternative cryogenic techniques: Mia et al. [7] reported considerable reductions in specific cutting energy and temperature during Ti-6Al-4V machining using liquid nitrogen jets; Jamil et al. [8] observed that CO_2-Snow delivers better surface quality and longer tool life compared to both MQL and cryogenic liquid nitrogen in titanium milling operations; Agrawal et al. [9] further validated the holistic advantages of cryogenic environments, including reduced tool wear, lower power consumption, and decreased carbon emissions. Despite these performance benefits, the implementation of such cryogenic systems involves greater technical complexity—requiring specialized infrastructure for the production, storage, and delivery of refrigerants—leading to higher capital investment and increased embedded energy demands. Although these technologies offer context-specific advantages, their sustainability performance is influenced by multiple factors—including material properties, process parameters, and system boundaries—and involves intricate trade-offs among environmental, economic, technical, and social dimensions. This multidimensional interplay presents significant challenges for objective technology selection and process optimization.

Consequently, developing a comprehensive evaluation framework capable of balancing multi-dimensional objectives and stakeholder interests has become essential for advancing sustainable clean cutting technologies. Current methodologies reflect diverse developments: in indicator systems and weight allocation, Tian et al. [10] integrated analytic hierarchy process (AHP), grey relational analysis, and TOPSIS to evaluate green product designs, while Bu et al. [11] applied the analytic hierarchy process–entropy weight method (AHP-EWM) to assess the influence of structural parameters on system performance. In modeling approaches, Rosiani et al. [12] combined sustainable value stream mapping with AHP to develop a manufacturing sustainability scoring system; Kluczek et al. [13] integrated life cycle assessment (LCA), life cycle cost (LCC), and social life cycle assessment (SLCA) to conduct energy-oriented sustainability evaluations; Fu et al. [14] proposed a set-pair analysis with entropy weighting to evaluate high-value tool remanufacturability. In decision and policy analysis, Chen et al. [15] employed evolutionary game theory to examine the impact of carbon taxes and subsidies on low-carbon behavior

in manufacturing enterprises, while Zhao et al. [16] used system dynamics to simulate the synergistic effects of incentive policies. Specifically for cooling strategy evaluation, Padhan et al. [17] applied the Pugh matrix to compare the sustainability performance of various cooling-lubrication methods, and Khan et al. [18] introduced a quantifiable Overall Performance Assessment Index (OPAI). The recently proposed Progressive Analysis of Key Sources (PACS) framework provides a systematic methodology for identifying and quantifying the core factors that most significantly affect sustainability during the processing stage. However, its capability to support multi-objective collaborative decision-making remains limited [19]. Despite these advancements, critical shortcomings persist: existing methods often rely excessively on subjective judgment or adopt purely data-driven models that deviate from engineering practicality; they fail to systematically resolve inherent conflicts among environmental, economic, technical, and social objectives; and crucially, they lack a transparent and interpretable mechanism for achieving dynamic equilibrium among competing stakeholders—leading to assessment outcomes with limited operational feasibility and low acceptance in real-world applications. These persistent deficiencies not only constrain the systematic and precise progression of clean cutting technologies toward sustainability but also highlight the urgent need for theoretical innovation and methodological advancement.

To address these gaps, this study proposes a novel multi-dimensional sustainability assessment framework integrating game-theoretic principles. First, a systematic indicator system is established across four dimensions: environmental impact, technical performance, economic efficiency, and social implications. Subjective and objective weights are determined using the AHP and EWM, respectively, followed by integration of the Nash equilibrium model from cooperative game theory to achieve balanced multi-objective coordination. The resulting Sustainability Index (SI) enables a holistic evaluation of cooling-lubrication strategies. Experimental studies on Ti-6Al-4V titanium alloy milling are conducted to compare the sustainability performance of dry milling, MQL, and CMQL under varying tool types and process parameters, aiming to provide a scientifically robust and practically applicable decision-support tool for green machining optimization.

The key contributions of this work are threefold:

1. A new weight coordination mechanism that integrates subjective-objective weighting with Nash bargaining theory, effectively addressing the critical challenge of resolving conflicts and imbalances in multi-dimensional sustainability assessment;
2. A comprehensive four-dimensional evaluation framework that enables full-scale quantification of the sustainability performance of cooling-lubrication processes;
3. An engineering-interpretable decision support framework that provides a quantifiable, transparent, and scientifically grounded basis for selecting optimal green machining technologies under diverse process conditions.

2. Development of a Sustainability Index Assessment Framework

To accurately assess the overall performance of manufacturing processes, a scientific and comprehensive sustainability evaluation framework is essential. Conventional approaches are typically confined to technical or economic dimensions, often neglecting environmental and social impacts. To address this limitation, this study proposes a four-dimensional assessment system based on the principle of coordinated "Environmental–Economic–Technical–Social" development, enabling systematic comparison of different clean cutting technologies and supporting informed decision-making in green manufacturing process selection. The sustainability evaluation framework is illustrated in Figure 1. It constitutes a structured, multi-level, method-integrated system encompassing nine quantifiable indicators across the four dimensions. Process data are collected through designed

experiments to ensure empirical validity. The core innovation lies in a three-stage integrated model that combines the AHP for subjective weighting, the EWM for objective weighting, and cooperative game theory for multi-objective coordination. This integration enables the calculation of a comprehensive Sustainability Index (SI), thereby establishing a transparent, traceable, and interpretable pathway from data acquisition to decision-making.

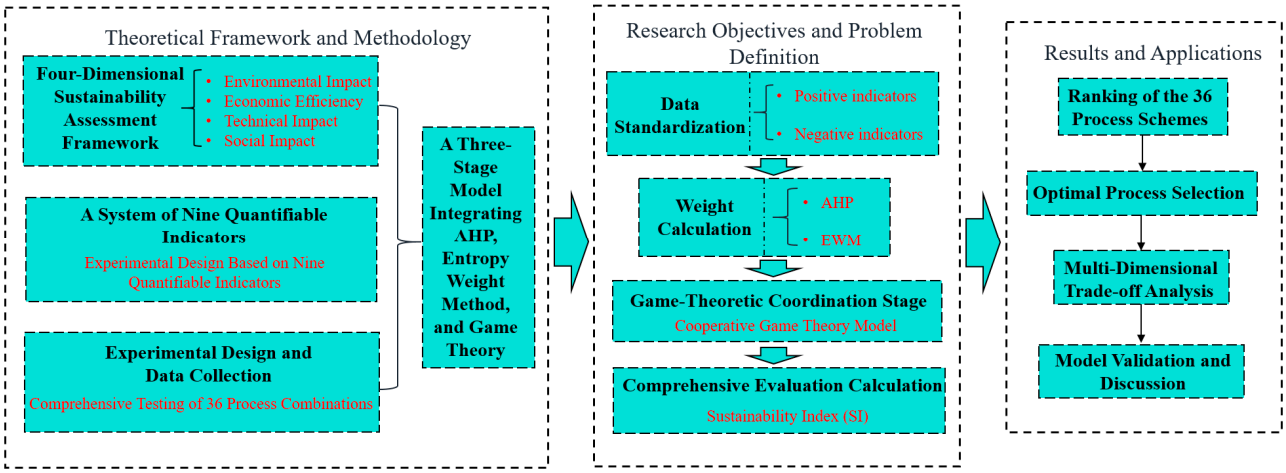


Figure 1. Sustainability assessment framework. Arrows indicate the logical flow and sequential steps of the assessment framework.

2.1. Establishment of Evaluation Dimensions

Based on the principles of systematicity, scientific rigor, operability, and directional guidance, this study establishes four primary indicators—environmental impact, technological impact, economic impact, and social impact—at the criterion level, which are further decomposed into nine quantifiable secondary indicators at the indicator level [20–22]. Figure 2 illustrates the configuration of sustainability indicators across the assessment dimensions. The framework enables a systematic linkage from macro-level strategy to practical implementation and from qualitative dimensions to quantitative metrics, seamlessly integrating comprehensive evaluation with process parameters to form a clear and operationally viable quantitative sustainability assessment system.

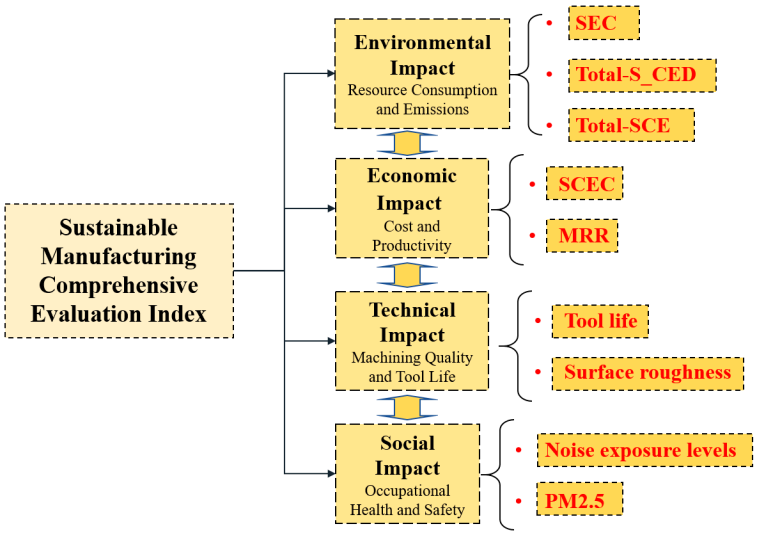


Figure 2. Sustainability indicators for evaluation dimensions. Arrows represent the interrelationships and trade-offs among the four sustainability dimensions.

2.2. Selection of Specific Evaluation Indicators

2.2.1. Environmental Impact Dimension

This dimension was designed to quantify the consumption of energy and resources during the machining processes, as well as its direct pressure on the natural environment. Accordingly, the following three indicators were selected:

Specific Energy Consumption (SEC): Defined as the total energy consumed per unit volume of material removed, this indicator directly reflects the overall energy utilization efficiency of the machining process. Lower SEC values correspond to higher energy efficiency. SEC is calculated as the ratio of the total energy consumption during machining to the volume of material removed.

$$SEC = \frac{E}{MRV} \tag{1}$$

where E represents the total energy consumption during machining (J) and MRV denotes the volume of material removed (mm^3).

Total Specific Cumulative Energy Demand (Total-S_CED): Defined as the sum of direct and indirect energy consumption per unit volume of material removed from a life-cycle perspective, this indicator accounts not only for the energy consumed during cutting but also for the embodied energy associated with upstream processes, such as tool manufacturing and the production of lubricants. Total-S_CED provides a more comprehensive measure of the true energy cost of the machining process.

$$Total - S_CED = \frac{E_{\text{direct}} + \sum E_{\text{indirect}_i}}{MRV} \tag{2}$$

where E_{direct} represents the machining energy consumption during the process, including all energy consumed by the machine tool during idle, cutting, and other operational stages (J); E_{indirect_i} denotes the sum of indirect energy consumed in all upstream processes, such as tool manufacturing and lubricant production (J); and MRV is the volume of material removed (mm^3).

$$E_{\text{direct}} = \int P(t)dt \tag{3}$$

where $P(t)$ represents the instantaneous power, which varies with time (W).

$$\sum E_{\text{indirect}_i} = E_{\text{tool}} + E_{\text{lubricant}} + E_{\text{workpiece}} \tag{4}$$

where E_{tool} denotes the embodied energy associated with tool manufacturing (J); $E_{\text{lubricant}}$ represents the embodied energy from the production of lubricants, including cutting oils and cryogenic media (J); and $E_{\text{workpiece}}$ corresponds to the embodied energy from the production of workpiece materials (J).

Total Specific Carbon Emissions (Total-SCE): Defined as the total carbon dioxide equivalent (CO_2-eq) emissions per unit volume of material removed, this indicator integrates both the carbon emissions from machining energy consumption and the indirect emissions associated with resource consumption. Total-SCE serves as a key metric for evaluating the greenhouse gas impact and overall environmental burden of the machining process.

$$Total - SCE = \frac{C_{\text{direct}} + \sum C_{\text{indirect}_i}}{MRV} \tag{5}$$

where C_{direct} represents the direct carbon emissions (kg) and C_{indirect_i} denotes the indirect carbon emissions (kg).

$$C_{\text{direct}} = E_{\text{direct}} \times EF_{\text{electricity}} \tag{6}$$

where $EF_{\text{electricity}}$ is the carbon emission factor of the electricity grid, with a value of 0.5703 kg CO_2/kWh [23].

$$\sum C_{\text{indirect}_i} = (m_{\text{tool}} \times EF_{\text{tool}}) + (V_{\text{lubricant}} \times EF_{\text{lubricant}}) + (m_{\text{workpiece}} \times EF_{\text{workpiece}}) \quad (7)$$

where m_{tool} is the tool wear mass (kg); EF_{tool} is the carbon emission factor of the tool (kg CO_2-eq/kg), with a value of 0.686 kg CO_2/kg; $V_{\text{lubricant}}$ represents the volume of lubricant consumed (L); $EF_{\text{lubricant}}$ is the carbon emission factor of the lubricant (kg CO_2-eq/L), with a value of 0.0747 kg CO_2/L; $m_{\text{workpiece}}$ denotes the mass of workpiece material consumed (kg); and $EF_{\text{workpiece}}$ is the carbon emission factor of the workpiece material (kg CO_2-eq/kg), with a value of 42.7447 kg CO_2/kg [24–27].

It should be noted that the environmental sustainability assessment in this study adopts a process-level system boundary, focusing on direct processing energy consumption and the energy and carbon emissions embodied in consumables such as cutting tools and lubricants used during the processing. In the cooling and lubrication system, liquid carbon dioxide is regarded as an externally supplied industrial medium, which is consistent with the assumption typically adopted in the sustainability assessment at the processing level. Therefore, upstream processes related to carbon dioxide production, liquefaction, large-scale transportation, and low-temperature infrastructure construction are not explicitly included. Although this boundary definition enables a fair comparison of different cooling and lubrication strategies under the same processing conditions, it may lead to an overestimation of the environmental performance of cooling and lubrication from a life-cycle perspective, which is recognized as a limitation of this study.

2.2.2. Economic Dimension

This dimension was designed to evaluate the economic feasibility of machining strategies in terms of production efficiency and resource consumption. The following two indicators were selected:

Total Specific Carbon Emission Cost (Total-SCEC): Defined as the carbon emission cost per unit volume of material removed under carbon trading or carbon tax mechanisms, this indicator internalizes environmental costs into economic metrics and reflects the economic competitiveness of machining strategies under low-carbon policies. Although both Total-SCEC and Total-SCE originate from carbon emissions, they represent different assessment dimensions: the former is a monetized indicator in the economic dimension, indicating the financial burden brought by carbon policies; the latter is a physical indicator in the environmental dimension, quantifying the greenhouse gas impact and overall environmental burden of the processing process. Together, they establish a comprehensive economic-environmental assessment framework, avoiding double counting and embodying the concept of internalizing external environmental costs into economic decisions.

$$Total - SCEC = Total - SCE \times P_{\text{carbon}} \quad (8)$$

where P_{carbon} represents the carbon price (RMB/kg CO_2-eq).

Material Removal Rate (MRR): Defined as the volume of material removed per unit time, this indicator directly determines production efficiency and serves as a key economic metric influencing production cycle and throughput. Higher MRR values generally correspond to lower time-related costs per part.

$$MRR = \frac{MRV}{t} \quad (9)$$

where t represents the effective net machining time (min).

2.2.3. Technical Performance Dimension

This dimension was designed to evaluate the technical performance of machining strategies in terms of machining efficiency, effectiveness, and resource utilization. The following two indicators were selected:

Tool Life: Defined as the total cutting length a single tool can achieve before failure, this indicator directly relates to tool replacement frequency, production costs, and machine downtime. It serves as a key metric for assessing the protective effect of cooling and lubrication strategies on cutting tools.

Surface Roughness: Defined as the microscopic unevenness of the machined workpiece surface, it is one of the most important indicators for evaluating machining quality and the final performance of the workpiece.

2.2.4. Social Impact Dimension

This study classifies "noise exposure level" and "$PM_{2.5}$ concentration" within the social impact dimension, as they represent direct occupational health hazards to on-site operators. As key Occupational Health and Safety (OSH) indicators, they reflect the immediate impact of manufacturing processes on workers' working environments, distinguishing this assessment from broader environmental pollution evaluations. This classification emphasizes a "human-centered" approach to social responsibility in the manufacturing process.

Noise Exposure Levels: Defined as the intensity of noise generated during the machining process, this indicator serves as an important basis for evaluating occupational health risks. Prolonged exposure to high noise levels can adversely affect operators' auditory systems and psychological well-being.

$PM_{2.5}$ Concentration: Defined as the mass concentration of particulate matter with an aerodynamic diameter of less than or equal to 2.5 μm in the machining area, these particles originate primarily from smoke and oil mist generated during machining. It directly reflects the impact of machining strategies on workplace air quality and poses significant respiratory health risks to operators.

In this study, the social sustainability dimension is represented by noise exposure levels and PM2.5 concentration, which are measurable indicators directly related to occupational health conditions in machining environments and are widely adopted in process-level sustainability assessments. However, these indicators serve as representative proxies rather than a comprehensive evaluation of all occupational safety and health risks. In particular, potential hazards associated with the handling of cryogenic media in CMQL systems, such as cold burns, high-pressure jet exposure, and accidental CO_2 leakage, are not explicitly assessed in the current framework. A comprehensive occupational safety evaluation would require dedicated risk analysis and safety modeling, which are beyond the scope of the present experimental study and are identified as an important direction for future research.

3. An Integrated Evaluation and Weight Coordination Framework Based on Game Theory

The development of a sustainability index for cooling and lubrication strategies represents a significant methodological challenge, particularly in the assignment of indicator weights. Conventional methods, such as AHP, rely inherently on subjective expert judgments, whereas entropy-based weighting approaches often fail to capture the priorities embedded in real-world decision-making contexts. This challenge is further exacerbated by the multidimensional nature of sustainability, which encompasses environmental, economic, technical, and social dimensions—each reflecting the distinct and frequently conflicting interests of key stakeholders, including governmental agencies, industrial enterprises, manufacturers, and local communities. Unlike conventional approaches that integrate

subjective and objective weights through rigid or additive rules, this study proposes a cooperative game-theoretic framework in which the four sustainability dimensions are conceptualized as rational agents engaged in a structured negotiation over weight allocation. The application of a Nash equilibrium solution enables the derivation of a balanced and mutually acceptable set of weights that reflect an equitable compromise among competing objectives. While the resulting sustainability index does not claim to yield a theoretically optimal outcome, it more accurately captures the inherent trade-offs present in practical decision-making environments, thereby providing a robust, empirically grounded, and policy-relevant basis for evaluating cooling and lubrication strategies.

3.1. Determination of Subjective Weights: Analytic Hierarchy Process (AHP)

AHP decomposes complex decision-making problems into a hierarchical structure and employs pairwise comparison matrices to derive the relative weights of individual elements [28]. The problem is typically organized into three levels: the goal level, representing the overall decision objective; the criteria level, encompassing the key factors necessary for achieving the goal; and the alternatives level, comprising the available options or solutions under evaluation.

3.1.1. Construction of Pairwise Comparison Matrices

Pairwise comparisons were conducted using Saaty's 1–9 scale [29] to construct the judgment matrix A.

$$A = \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1n} \\ a_{21} & a_{22} & \cdots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{n1} & a_{n2} & \cdots & a_{nn} \end{bmatrix} \tag{10}$$

where a_{ij} represents the relative importance of element i with respect to element j, and the matrix satisfies $a_{ij} = \frac{1}{a_{ji}}$.

The 1–9 scale is defined as follows: a value of 1 indicates that the two elements are equally important; a value of 3 indicates that element i is slightly more important than element j; a value of 5 indicates that element i is moderately more important than element j; a value of 7 indicates that element i is strongly more important than element j; a value of 9 indicates that element i is extremely more important than element j; and values of 2, 4, 6, and 8 represent intermediate judgments between adjacent criteria.

3.1.2. Calculation of the Weight Vector

The weight vector of the judgment matrix was calculated using the square root method, and the resulting vector was normalized to obtain the relative weights of the individual elements.

$$\overline{w}_i = \left(\prod_{j=1}^{n} a_{ij} \right)^{1/n}, \quad i = 1, 2, \ldots, n \tag{11}$$

where $\overline{w}_i$ denotes the geometric mean of the elements in the ith row of the judgment matrix.

$$W_{sub} = \left[\frac{\overline{w}_1}{\sum_{i=1}^{n} \overline{w}_i}, \frac{\overline{w}_2}{\sum_{i=1}^{n} \overline{w}_i}, \ldots, \frac{\overline{w}_n}{\sum_{i=1}^{n} \overline{w}_i} \right]^T \tag{12}$$

where W_{sub} denotes the eigenvector (weight vector) obtained by normalizing the vector $\overline{w}_i$.

3.1.3. Consistency Check

To ensure the logical consistency of the pairwise comparisons, a consistency check was conducted.

$$\lambda_{\max} = \frac{1}{n}\sum_{i=1}^{n}\frac{(AW)_i}{w_i} \tag{13}$$

where $(AW)_i$ represents the ith element of the vector AW.

The consistency index (CI) was calculated as follows:

$$CI = \frac{\lambda_{\max} - n}{n-1} \tag{14}$$

The average random consistency index (RI) was obtained from the standard reference table.

$$RI = \begin{cases} 0.00 & n = 1 \\ 0.00 & n = 2 \\ 0.58 & n = 3 \\ 0.90 & n = 4 \\ 1.12 & n = 5 \\ 1.24 & n = 6 \\ 1.32 & n = 7 \\ 1.41 & n = 8 \\ 1.45 & n = 9 \\ 1.49 & n = 10 \end{cases} \tag{15}$$

The consistency ratio (CR) was calculated as follows:

$$CR = \frac{CI}{RI} \tag{16}$$

If $CR < 0.1$, the consistency of the judgment matrix was considered acceptable; otherwise, the matrix needed to be revised.

3.2. Determination of Objective Weights: Entropy Weight Method (EWM)

EWM is an objective weighting approach based on information entropy, which determines the weights of indicators by quantifying the degree of dispersion in their data. Indicators with smaller entropy values provide greater amounts of information and, consequently, should be assigned higher weights in the comprehensive evaluation [30]. The steps for weight allocation using the EWM are as follows:

3.2.1. Data Normalization

Benefit Indicators:

$$Y_{ij} = \frac{x_{ij} - \min(x_j)}{\max(x_j) - \min(x_j)} \tag{17}$$

Cost Indicators:

$$Y_{ij} = \frac{\max(x_j) - x_{ij}}{\max(x_j) - \min(x_j)} \tag{18}$$

where x_{ij} represents the original value of the jth indicator for the ith sample, Y_{ij} denotes the normalized value, and $\max(x_j)$ and $\min(x_j)$ are the maximum and minimum values of the jth indicator across all samples, respectively.

3.2.2. Calculation of Indicator Entropy

The calculation method for the entropy value e_j of the jth indicator is as follows:

$$p_{ij} = \frac{Y_{ij}}{\sum_{i=1}^{m} Y_{ij}} \tag{19}$$

where p_{ij} represents the proportion of the ith sample under the jth indicator.

$$e_j = -\frac{1}{\ln m} \sum_{i=1}^{m} p_{ij} \ln p_{ij} \tag{20}$$

when $p_{ij} = 0$, it is defined that $p_{ij} \ln p_{ij} = 0$; e_j denotes the entropy of the jth indicator.

$$g_j = 1 - e_j \tag{21}$$

where g_j represents the coefficient of variation of the jth indicator. A larger g_j indicates that the indicator provides more information and, consequently, should be assigned a higher weight.

3.2.3. Calculation of Indicator Weights

$$W_{obj} = \frac{g_j}{\sum_{k=1}^{n} g_k} = \frac{1 - e_j}{\sum_{k=1}^{n} (1 - e_k)} \tag{22}$$

where W_{obj} denotes the entropy-based weight of the jth indicator.

3.3. Weight Coordination Model Based on Cooperative Game Theory

In this study, four evaluation dimensions were treated as four players in a cooperative game, with each player seeking to maximize the share of its subordinate indicators in the final weight allocation [31]. A Nash equilibrium model was employed to identify an equilibrium solution acceptable to all parties.

3.3.1. Determination of Initial Indicator Weights for Each Player

$$W_0^{(k)} = a \cdot W_{\text{subj}}^{(k)} + (1 - a) \cdot W_{\text{obj}}^{(k)} \tag{23}$$

where $W_0^{(k)}$ denotes the initial weight claim of the kth dimension, and a represents the scaling coefficient. In this study, a was set to 0.6.

3.3.2. Minimum Guarantee Requirement and Equilibrium Power

To ensure the basic interests of each dimension, a minimum guarantee requirement d_k was introduced, representing the lowest weight share that the dimension must receive regardless of the negotiation outcome [32]. In this study, d_k was set as a proportion of the AHP-derived weight for each dimension, reflecting a fundamental respect for expert judgment.

$$d_k = \delta \cdot W_{\text{subj}}^{(k)}, \quad 0 < \delta < 1 \tag{24}$$

where δ is the guarantee coefficient, which was set to 0.6 in this study.

Based on the dual-carbon objectives and the requirements for high-quality development, different equilibrium power coefficients were assigned to each dimension. The coefficients were set as follows:

$$\lambda = [\lambda_1, \lambda_2, \lambda_3, \lambda_4] = [0.30, 0.25, 0.25, 0.20] \tag{25}$$

3.3.3. Establishment of the Nash Equilibrium Model

Maximization of the Nash product objective function:

$$\max_w \prod_{k=1}^{4} (U_k(W) - d_k)^{\lambda_k} \tag{26}$$

where $U_k(W) = \sum_{i \in I_k} w_i$ denotes the utility function of player k, and I_k represents the set of indicators belonging to dimension k.

Equivalent logarithmic form:

$$\max_W \sum_{k=1}^{4} \lambda_k \ln(U_k(W) - d_k) \tag{27}$$

Constraint conditions:

$$\begin{cases} \sum_{j=1}^{9} w_j = 1 \\ w_j \geq 0, \quad j = 1, 2, \ldots, 9 \\ U_k(W) > d_k, \quad k = 1, 2, 3, 4 \end{cases} \tag{28}$$

3.3.4. Analytical Solution

Construction of the Lagrangian function:

$$L(W, \mu) = \sum_{k=1}^{4} \lambda_k \ln(U_k(W) - d_k) + \mu \left(1 - \sum_{j=1}^{9} w_j\right) \tag{29}$$

Partial derivative with respect to the weight w_j belonging to dimension K:

$$\frac{\partial L}{\partial w_j} = \frac{\lambda_K}{U_k(W) - d_k} - \mu = 0 \tag{30}$$

Thus, $U_K - d_k = \lambda_K / \mu$ can be obtained. By substituting the constraints: $\sum_{k=1}^{4} U_k = 1$, $\sum_{k=1}^{4} d_k = \delta$. The solution is: $\mu = 1/(1-\delta)$, yielding the equilibrium utility as U_k^*.

$$U_k^* = d_k + (1 - \delta) \cdot \lambda_k \tag{31}$$

3.3.5. Calculation of the Final Indicator Weights w_j^*

The equilibrium utility determines the weight budget allocated to each dimension. Dimension k then distributes its budget U_k^* among its subordinate indicators in proportion to their initial preference vector $W_0^{(k)}$.

$$w_j^* = U_k^* \times w_{0j}^{(k)}, \quad \forall j \in I_k \tag{32}$$

where $w_{0j}^{(k)}$ denotes the element corresponding to indicator j in the initial strategy vector of dimension k.

3.3.6. Sustainability Index Calculation

The sustainability index of each machining strategy was calculated by integrating the comprehensive indicator weights with the corresponding normalized indicator values.

$$SI_i = \sum_{j=1}^{9} w_j^* \cdot Y_{ij} \tag{33}$$

The machining strategies were ranked in descending order according to their corresponding sustainability index values (SI_i). The strategy with the highest SI_i was identified as the optimal sustainable manufacturing process.

3.4. Sensitivity Analysis of the Initial Weight Coefficient a and the Minimum Guarantee Coefficient δ

To ensure the robustness of the game theory coordination model and avoid the subjective arbitrariness in parameter selection, this section establishes a sensitivity analysis framework for α and δ. α (the initial weight coefficient) controls the balance between subjective and objective weights, while δ (the minimum guarantee coefficient) ensures the basic interests of each evaluation dimension. The sensitivity analysis aims to verify the stability of the sustainability assessment results when these two key parameters vary within a reasonable range. The analysis framework is as follows:

(1) Parameter range setting: α and δ are respectively taken from {0.4, 0.5, 0.6, 0.7, 0.8}, forming 5 × 5 = 25 parameter combinations.

(2) Evaluation indicators:

- Ranking stability was evaluated by observing changes in the ordinal position of the benchmark optimal solution across different parameter combinations.
- Order consistency was assessed using Spearman's rank correlation coefficient to quantify the degree of agreement between rankings derived under each parameter set and the reference ranking.

4. Experimental Design

To systematically obtain multidimensional performance data of different cooling and lubrication strategies and to support the calculation of the sustainability index as well as the validation of the proposed model, this section details the experimental setup, workpiece materials, machining parameters, and data acquisition procedures.

4.1. Experimental Equipment, Materials, and Data Acquisition

4.1.1. Machine Tool and Data Acquisition Scheme

The milling experiments on Ti-6Al-4V titanium alloy were conducted on a VC1060 vertical machining center (Nanjing Ningqing CNC Machine Tool Manufacturing Co., Ltd., Nanjing, China). To enable comprehensive and quantitative assessment of sustainability indicators, the experimental setup integrated a synchronized suite of high-precision instruments: tool flank wear was monitored in situ using an OLYMPUS BX53M optical microscope (Olympus Corporation, Tokyo, Japan), with tool life defined as the machining time required to reach a flank wear width (VB) of 0.3 mm—per ISO 8688-2 [33], the internationally recognized standard for tool life determination in milling operations; surface roughness (Ra) of the machined workpiece was measured using a TR200 profilometer (Wuxi Sengan Mechanical Measuring Instrument Co., Ltd. Wuxi, China), with five independent

traversals per test location and arithmetic averaging to ensure measurement repeatability and statistical reliability; real-time active power consumption was acquired via a calibrated YP9830 three-phase energy meter(Anhui Hongba Machinery Equipment Co., Ltd. Fuyang, China)—recording voltage, current, and power factor—to enable accurate energy accounting and subsequent carbon emission estimation based on region-specific grid emission factors; noise exposure at the operator position was recorded at a 1 Hz sampling frequency, sufficient to capture transient acoustic events without aliasing; $PM_{2.5}$ concentration was monitored at two spatial locations (0.5 m and 1.0 m from the machining zone) using traceable optical particle sensors to characterize the spatial gradient of particulate dispersion. All instruments underwent pre-experiment calibration with documented metrological traceability, as shown in Figure 3. This integrated, multi-parameter monitoring strategy delivers temporally aligned, metrologically robust data essential for rigorous, quantitative sustainability analysis.



Figure 3. Experimental equipment.

4.1.2. Cutting Tool Specifications and Workpiece Material

Two commonly used types of cutting tools were employed for comparative investigation: solid end mills and indexable milling inserts, each in both uncoated and AlTiN-coated conditions. Their detailed specifications are presented in Table 1.

The workpiece material selected was Ti-6Al-4V alloy, which is widely applied in the aerospace industry due to its high strength and favorable machinability. The chemical composition of the Ti-6Al-4V alloy is given in Table 2.

Table 1. Specifications of cutting tools used in the experiments.

Tool Type	Specific Tool Type	Coating	Key Specifications (mm)
End Mill	4-flute flat end mill	Uncoated AlTiN-coated	Diameter: 14
Milling Insert	Square milling insert	Uncoated AlTiN-coated	Nose radius: 0.2

All workpieces were prepared as rectangular blocks with uniform dimensions of 100 mm × 100 mm × 40 mm. The difficult-to-machine nature of Ti-6Al-4V, characterized by its low thermal conductivity and high strength, presents significant challenges in terms

of tool wear and energy consumption. This makes it an ideal candidate for evaluating the sustainability of different clean cutting techniques. The cutting tools and workpiece are shown in Figure 4.

Table 2. Chemical composition of Ti-6Al-4V alloy.

Element	Ti	Al	V	Fe	O	C	N	H	Other Elements
wt.%	Allowance	5.50–6.75	3.50–4.50	≤0.30	≤0.20	≤0.08	≤0.05	≤0.015	≤0.10

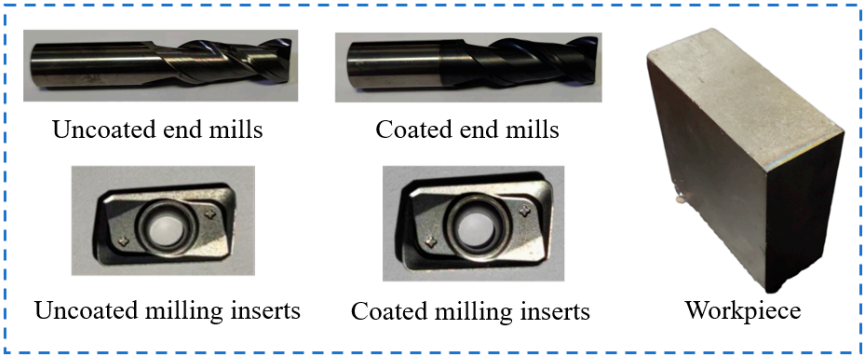


Figure 4. Cutting tools and workpiece.

4.1.3. Lubricants and Lubrication Systems

MQL system: An externally mixed MQL system was employed, with a delivery pressure ranging from 60 to 80 bar and a lubricant flow rate set at 50 mL/h. An environmentally benign vegetable-based lubricant specifically formulated for MQL applications was used.

CMQL system: Based on the MQL configuration, a cryogenic CO_2 injection unit was integrated. Cryogenic CO_2 was supplied through a cryogenic jet nozzle and co-injected with the lubricant aerosol, enabling simultaneous cooling and lubrication during the machining process. Figure 5 illustrates the configurations of the MQL and CMQL systems.

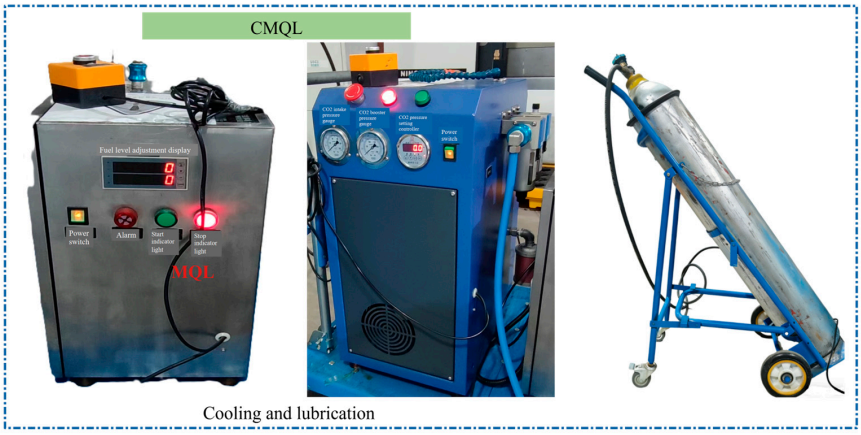


Figure 5. MQL and CMQL systems.

4.2. Machining Parameter Settings

A full factorial experimental design with three factors was employed to investigate the effects of individual factors and their interactions on the sustainability indicators. The specific machining parameters are listed in Table 3. Each experiment was performed using a new cutting edge, which was operated until either the end-of-life criterion for the tool was reached or the preset cutting length was completed. In total, 36 independent machining combinations were generated, corresponding to 3 lubrication strategies × 3 cutting speeds × 4 tool types.

Table 3. Processing parameters.

Factor	Level 1	Level 2	Level 3	Level 4
Tool type	Uncoated end mills	Coated end mill	Uncoated insert	Coated insert
Lubrication	Dry	MQL	CMQL	-
Milling speed	100 (m/min)	130 (m/min)	160 (m/min)	-

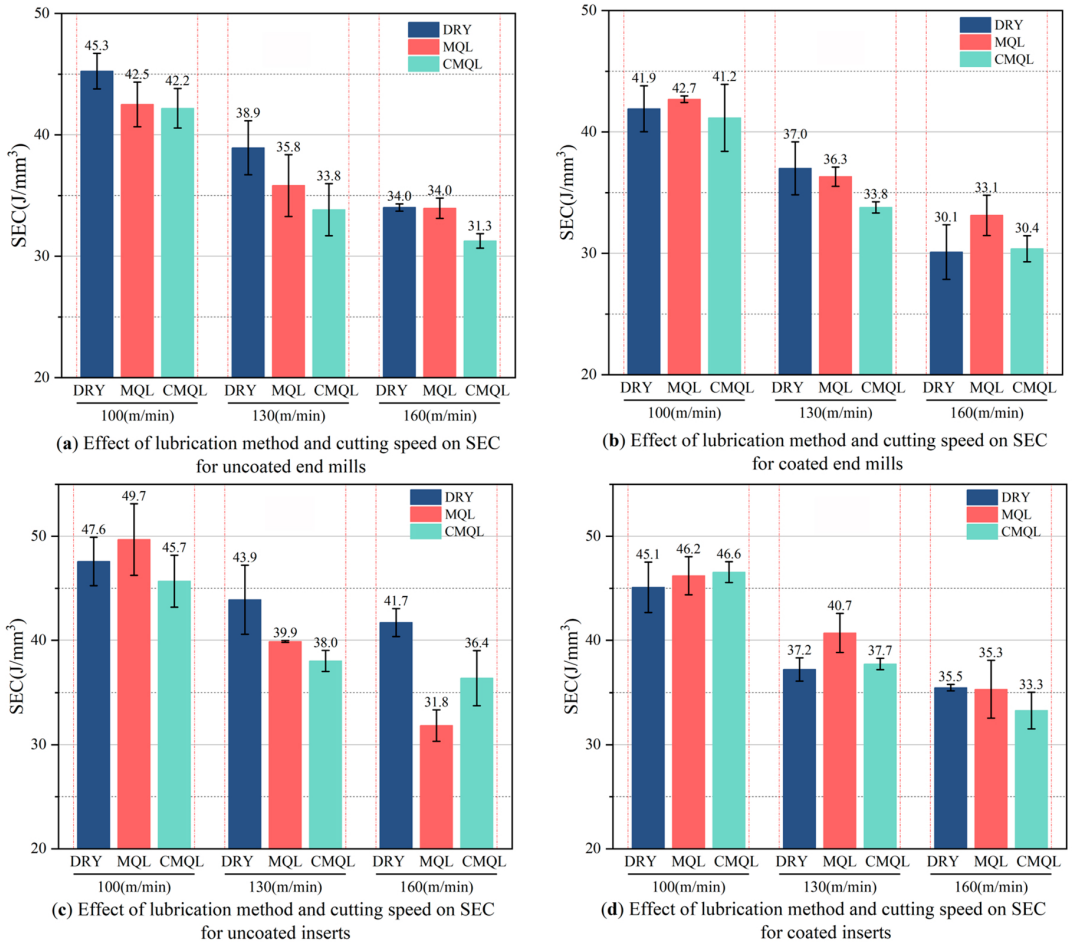
5. Experimental Results and Analysis

5.1. Analysis of Environmental Impact Indicators

Within the environmental impact indicators, significant differences were observed among the cooling and lubrication strategies, which were further affected by tool type and cutting speed. Dry milling exhibited the highest environmental impact, indicating the greatest ecological burden. In contrast, MQL and CMQL markedly reduced energy consumption and carbon emissions when combined with coated tools under medium-to-high cutting speeds, with CMQL demonstrating the most favorable environmental performance.

5.1.1. Specific Energy Consumption (SEC)

Figure 6 presents the effects of different tool types, lubrication methods, and cutting speeds on the SEC. As the cutting speed increased, the material removal efficiency improved, resulting in a reduction of energy consumption per unit volume. CMQL achieved the highest energy efficiency by reducing frictional heat and cutting forces through low-temperature cooling. Additionally, coated tools exhibited lower SEC values due to their reduced friction coefficient, further enhancing overall energy performance.



(a) Effect of lubrication method and cutting speed on SEC for uncoated end mills

(b) Effect of lubrication method and cutting speed on SEC for coated end mills

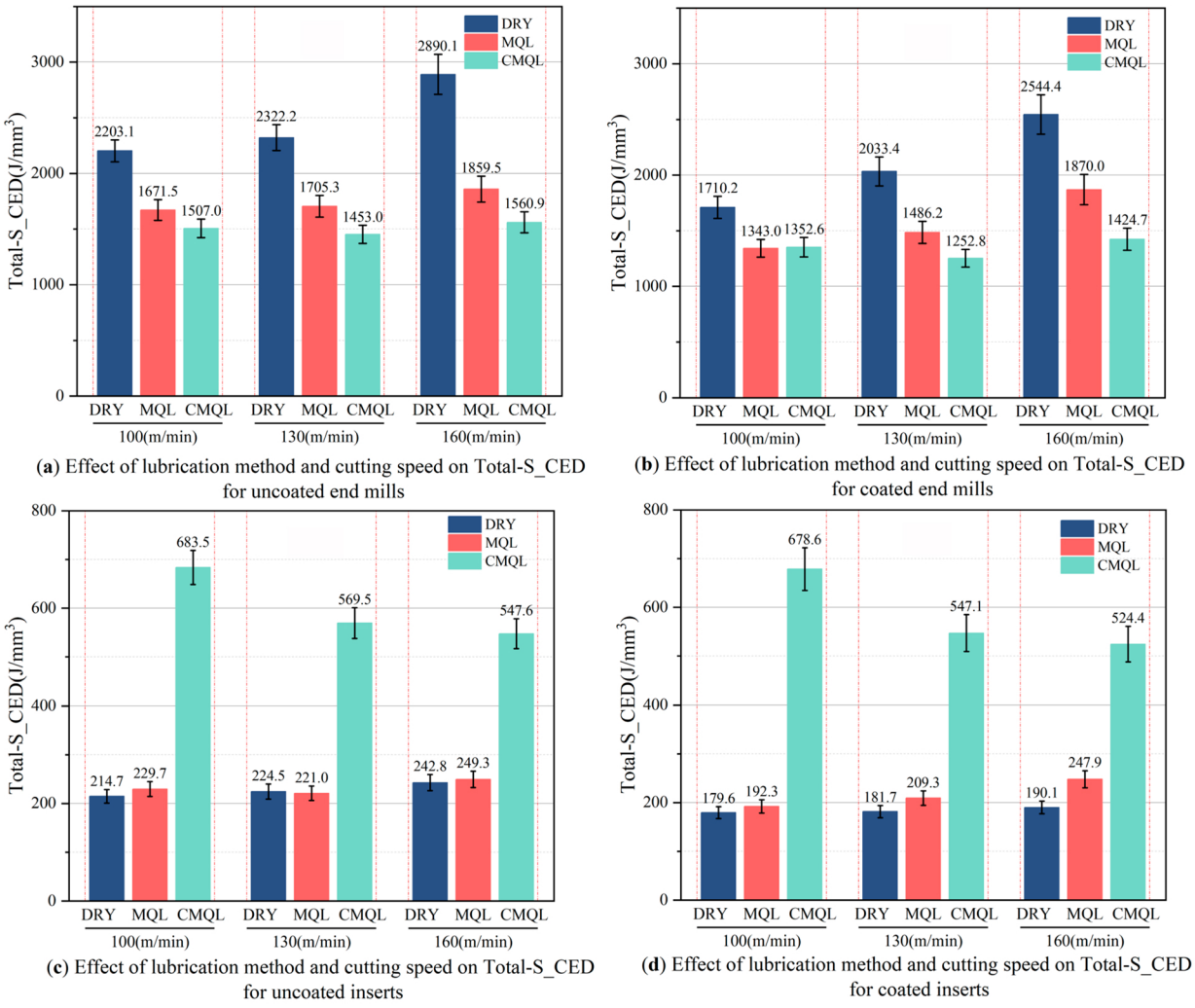
(c) Effect of lubrication method and cutting speed on SEC for uncoated inserts

(d) Effect of lubrication method and cutting speed on SEC for coated inserts

Figure 6. Effects of tool type, lubrication method, and cutting speed on the SEC.

5.1.2. Total Specific Cumulative Energy Demand (Total-S_CED)

Figure 7 compares the effects of different tool types, lubrication methods, and cutting speeds on Total-S_CED. It demonstrates that the CMQL process significantly extends tool life, thereby reducing the embodied energy associated with tool manufacturing and replacement. Meanwhile, due to their simpler structure and lower production energy requirements, blade-type tools typically exhibit lower Total-S_CED in conventional machining compared to more complex end mills. However, the CMQL system incorporates additional processes—such as low-temperature cooling, lubricant preparation, and delivery—that introduce substantial embodied energy over the full life cycle. In blade processing, where baseline manufacturing energy is inherently low, this system-related energy constitutes a relatively high proportion, leading to higher Total-S_CED under CMQL conditions than under dry milling or MQL conditions.



(a) Effect of lubrication method and cutting speed on Total-S_CED for uncoated end mills

(b) Effect of lubrication method and cutting speed on Total-S_CED for coated end mills

(c) Effect of lubrication method and cutting speed on Total-S_CED for uncoated inserts

(d) Effect of lubrication method and cutting speed on Total-S_CED for coated inserts

Figure 7. Effects of tool type, lubrication method, and cutting speed on the Total-S_CED.

5.1.3. Total Specific Carbon Emissions (Total-SCE)

Figure 8 compares the effects of different tool types, lubrication methods, and cutting speeds on Total-SCE. The results indicate that the carbon emission trend is largely consistent with that of the energy consumption index, primarily due to shared sources such as electrical energy consumption during cutting and embodied carbon emissions associated with tool manufacturing. The CMQL lubrication method reduces both direct power consumption and indirect material-related embodied carbon emissions by improving energy efficiency and extending tool life. Furthermore, owing to their simpler structure and lower

production-related carbon emissions, blade-type tools exhibit a smaller unit processing carbon footprint than more complex end mills, demonstrating superior carbon emission performance across all machining conditions.

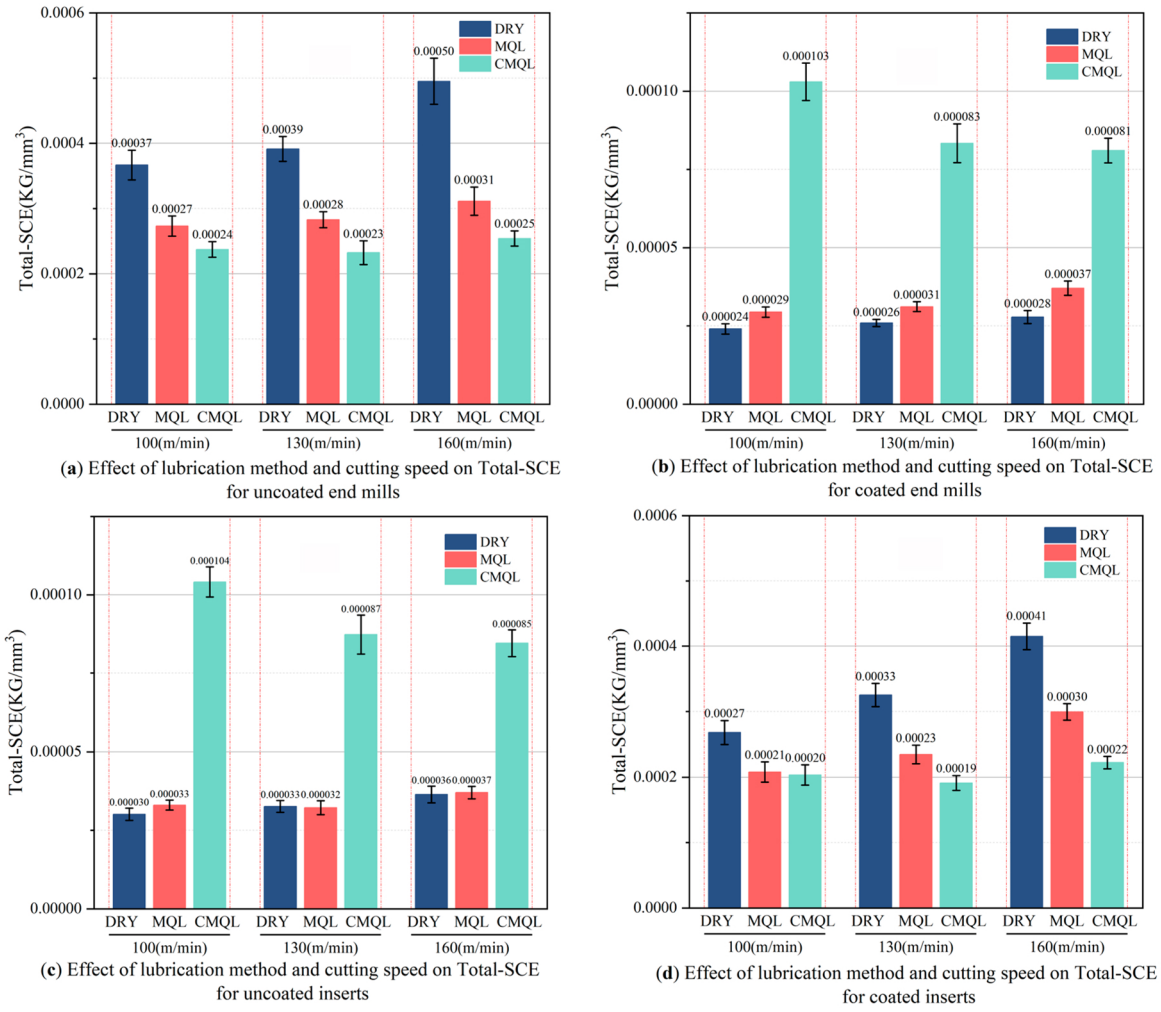


Figure 8. Effects of tool type, lubrication method, and cutting speed on the Total-SCE.

5.2. Analysis of Economic Impact Indicators

From an economic perspective, both the cooling–lubrication method and cutting speed jointly influenced machining efficiency and associated costs. Dry milling eliminated the cost of cutting fluids but incurred higher tool wear. In contrast, MQL and CMQL, when used with coated tools at medium-to-high cutting speeds, enhanced MRR and reduced unit costs, thereby demonstrating superior economic performance.

The material removal rate was solely dependent on cutting speed, with higher speeds resulting in increased MRR. Regarding Total-SCEC, Figure 9 quantifies the influence of tool type, lubrication strategy, and cutting speed on Total-SCEC. CMQL consistently achieves the lowest Total-SCEC across most tool configurations—primarily by suppressing cutting-zone temperature rise and interfacial friction, thereby reducing both tool wear and process energy demand. Notably, however, this advantage reverses for insert tools: CMQL's aggressive cooling induces thermal shock at the cutting edge and incurs disproportionately high auxiliary system costs (e.g., refrigeration, fluid conditioning, and high-pressure delivery), resulting in a net increase in Total-SCEC. In contrast, inserts achieve substantially lower Total-SCEC than solid end mills owing to modular design advantages—including reduced raw material consumption, shorter tool change times, minimized non-cutting downtime,

and improved tool life predictability—while coated variants further enhance economic performance through friction reduction, wear resistance, and extended service life. The effect of cutting speed is inherently non-linear: a moderate range centered at approximately 130 m/min optimally balances specific energy consumption, machining productivity (measured as material removal rate per unit time), and tool wear rate—yielding the lowest achievable Total-SCEC under representative operational constraints, including prescribed tool life targets and surface integrity requirements.

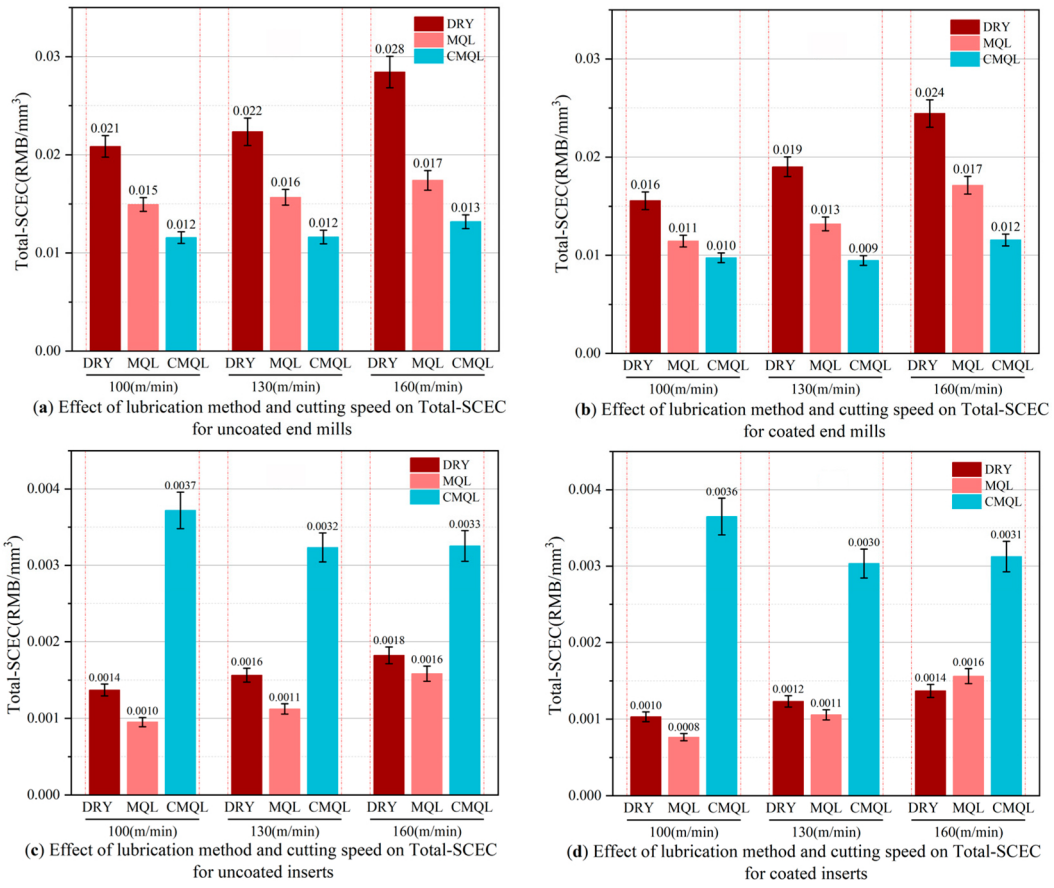


Figure 9. Effects of tool type, lubrication method, and cutting speed on the Total-SCEC.

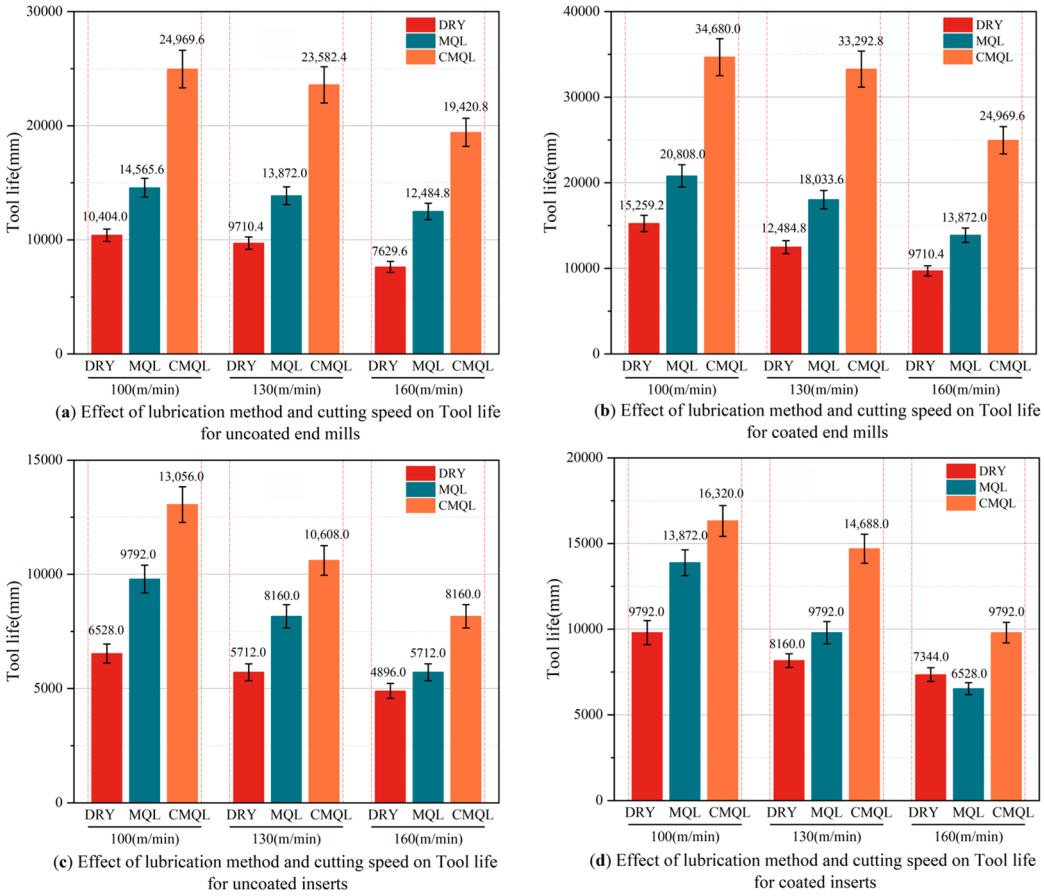
5.3. Analysis of Technical Performance Impact Indicators

The technical performance was jointly influenced by the cooling and lubrication strategy, tool type, and cutting speed. Under dry milling conditions, tool life was short and surface quality was poor. MQL and CMQL significantly extend tool life and improve surface finish, particularly when used in conjunction with coated tools at optimal cutting speeds, where CMQL exhibits the most pronounced performance advantages.

5.3.1. Tool Life

Figure 10 illustrates the effects of tool type, lubrication strategy, and cutting speed on tool life. As shown, CMQL significantly extends tool life relative to dry and conventional flood cooling conditions—primarily by suppressing cutting-zone temperature and promoting the formation of a stable, load-bearing lubricating film at the tool–chip interface, thereby concurrently mitigating thermal loading and friction-driven wear. Under CMQL, coated tools consistently outperform uncoated counterparts across all tested cutting speeds, indicating a strong synergistic interaction between the coating's intrinsic wear resistance and thermal barrier capability and the enhanced cooling–lubrication performance of CMQL. In contrast, increasing cutting speed intensifies thermo-mechanical loading and accelerates

wear progression, leading to a monotonic decrease in tool life regardless of lubrication method or tool configuration. Collectively, tool life is governed by the coupled influence of lubrication strategy, tool substrate/coating architecture, and cutting parameters; among all combinations evaluated, CMQL paired with coated tools delivers the greatest tool life extension—particularly at low-to-medium cutting speeds, where thermal management dominates wear mechanisms.



(a) Effect of lubrication method and cutting speed on Tool life for uncoated end mills

(b) Effect of lubrication method and cutting speed on Tool life for coated end mills

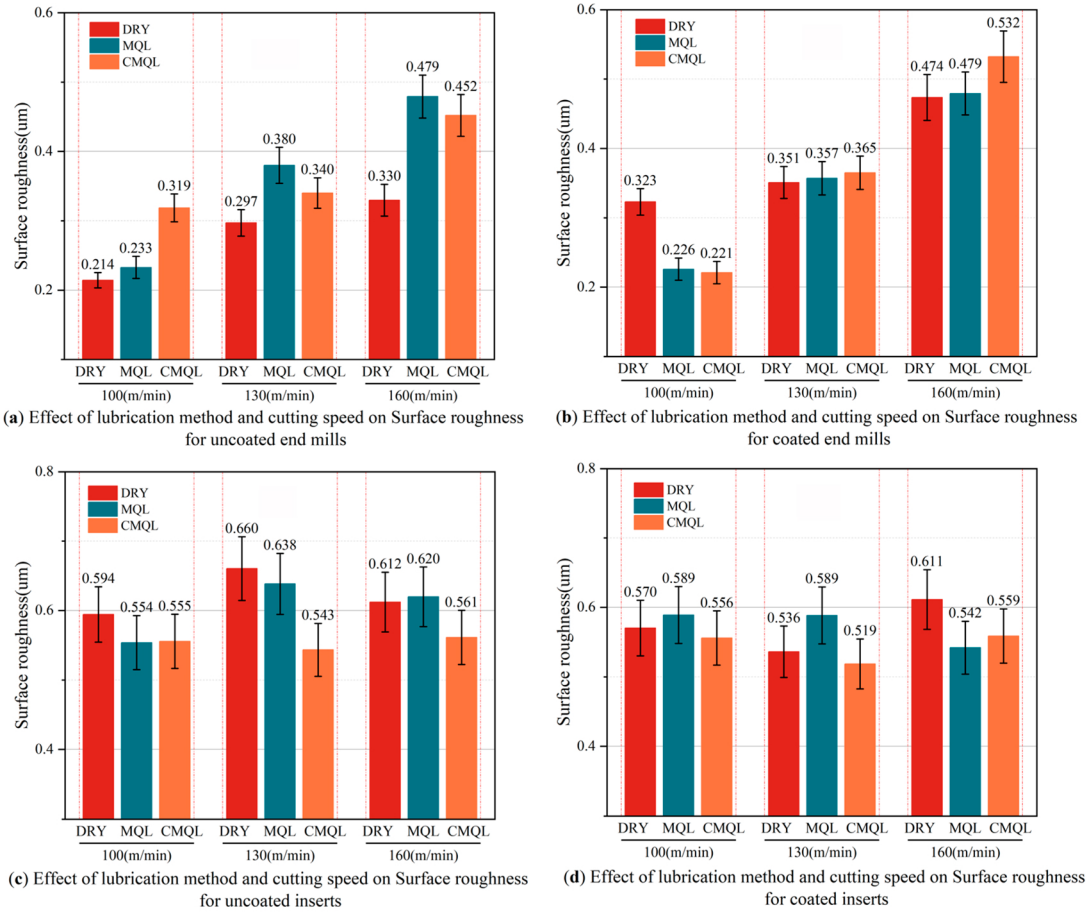
(c) Effect of lubrication method and cutting speed on Tool life for uncoated inserts

(d) Effect of lubrication method and cutting speed on Tool life for coated inserts

Figure 10. Effects of tool type, lubrication method, and cutting speed on the tool life.

5.3.2. Surface Roughness

Figure 11 presents the effects of tool type, lubrication strategy, and cutting speed on surface roughness. As shown, surface roughness is strongly governed by the coupled influence of lubrication strategy, tool substrate/coating architecture, and cutting speed. Under CMQL conditions, the synergistic cooling and lubrication action effectively suppresses cutting-zone temperature rise and inhibits built-up edge (BUE) formation—thereby stabilizing the material removal process and improving surface finish. At lower cutting speeds, reduced thermal deformation and suppressed chatter-related dynamic instability yield smoother machined surfaces; in contrast, increasing cutting speed intensifies thermal accumulation and exacerbates tool–workpiece vibratory interaction, accelerating flank and crater wear and promoting surface irregularities such as feed marks and micro-tearing. Compared with uncoated tools, coated tools provide a lower and more stable coefficient of friction due to their superior wear resistance and chemical inertness at elevated temperatures—contributing to sustained cutting edge sharpness and attenuated cutting force fluctuations. Overall, the results demonstrate that the combined use of CMQL and coated tools achieves the lowest and most consistent surface roughness values—particularly within the low-to-medium cutting speed range, where thermal–mechanical stability governs surface integrity.



(a) Effect of lubrication method and cutting speed on Surface roughness for uncoated end mills

(b) Effect of lubrication method and cutting speed on Surface roughness for coated end mills

(c) Effect of lubrication method and cutting speed on Surface roughness for uncoated inserts

(d) Effect of lubrication method and cutting speed on Surface roughness for coated inserts

Figure 11. Effects of tool type, lubrication method, and cutting speed on the surface roughness.

5.4. Analysis of Social Impact Indicators

In the social impact dimension, both noise levels and $PM_{2.5}$ concentrations were influenced by the lubrication method and cutting speed. Noise levels showed minor variation across the three lubrication strategies. Although MQL provided effective cooling, it generated substantially higher $PM_{2.5}$ concentrations. In contrast, CMQL demonstrated the most significant reduction in particulate matter, with $PM_{2.5}$ values markedly lower than those under MQL, while maintaining controllable noise levels. This indicates superior occupational health protection performance.

5.4.1. Noise Exposure Levels

Figure 12 presents the effects of tool coating, lubrication strategy, and cutting speed on noise exposure levels. As confirmed experimentally, noise exposure increases significantly with rising cutting speed—primarily driven by amplified structural vibrations and intensified dynamic cutting forces. Among lubrication strategies, dry cutting yields the lowest noise level, as it eliminates auxiliary fluid injection and all associated aerodynamic noise sources unconditionally. In contrast, MQL and CMQL operate via fundamentally distinct noise generation mechanisms: MQL noise originates predominantly from intermittent lubricant atomization and pulsating carrier air flow, whereas CMQL produces elevated broadband aerodynamic noise due to its higher operating air pressure and greater volumetric flow rate—particularly at high cutting speeds. Tool coating plays a decisive role in noise suppression: coated tools reduce interfacial friction at both the tool–chip and tool–workpiece interfaces, thereby suppressing vibration amplitude and attenuating high-frequency noise components; consequently, coated tools consistently exhibit lower noise levels than uncoated tools across all experimental conditions. For low-noise machin-

ing, dry cutting combined with coated tools is recommended for medium- and low-speed regimes. When cooling-lubrication is unavoidable, CMQL must be subjected to rigorous, operationally representative evaluation—not only for its superior heat extraction capacity but also for its quantifiable contribution to total noise emission—to ensure an optimal balance between thermal performance and regulatory acoustic compliance.

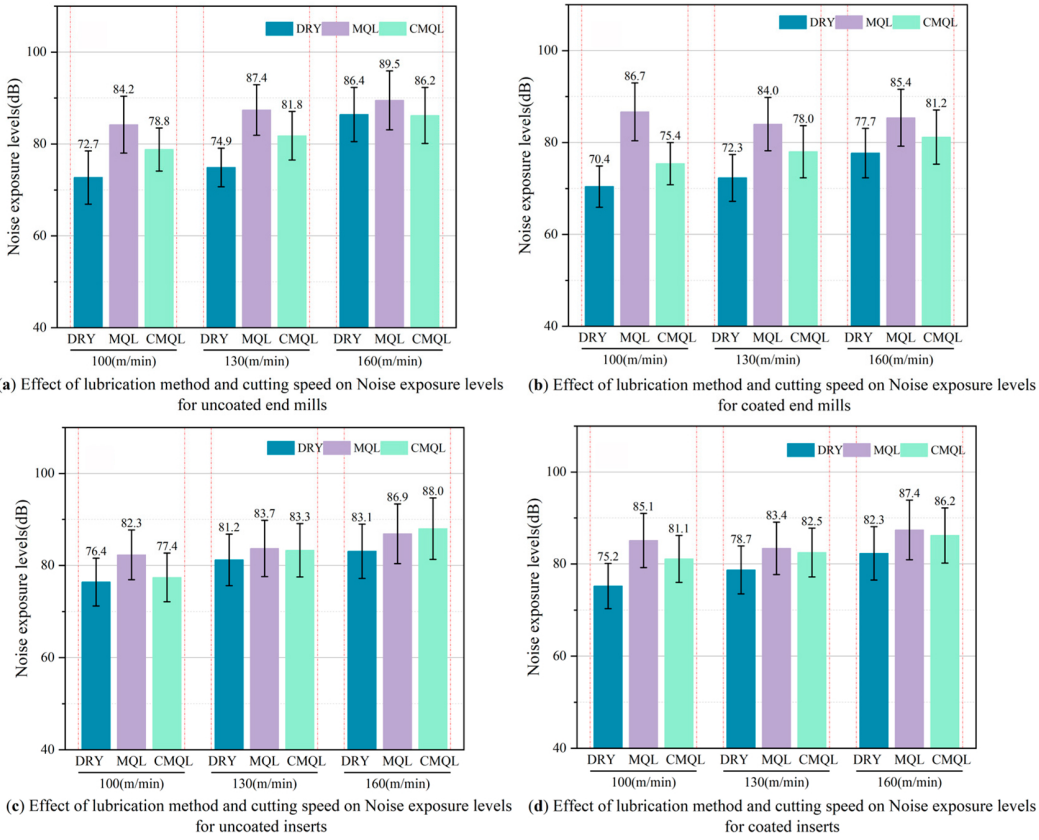


Figure 12. Effects of tool type, lubrication method, and cutting speed on the noise exposure levels.

5.4.2. $PM_{2.5}$ Concentration

Figure 13 illustrates the significant influence of different tool types, lubrication strategies, and cutting speeds on the $PM_{2.5}$ concentration in the processing area. The experiments show that the $PM_{2.5}$ concentration is mainly affected by the lubrication method, and is basically unrelated to the change in cutting speed. Dry cutting, as it does not use any cutting fluid, only generates a very small amount of wear particles from the workpiece and the tool, thus maintaining a very low $PM_{2.5}$ concentration (approximately 0.010–0.011 g per cubic meter). In contrast, MQL reduces the amount of liquid used by atomizing the lubricating oil and spraying it into the cutting area. Although this reduces the amount of liquid, it generates a large amount of inhalable oil mist suspended particles, resulting in a significant increase in $PM_{2.5}$ concentration (generally higher than 2.19 g per cubic meter). CMQL, by utilizing the condensation effect of its low-temperature medium, promotes the easier aggregation and sedimentation of oil mist particles, while inhibiting the evaporation and refinement of the lubricating medium. Therefore, the $PM_{2.5}$ concentration is significantly lower than that of MQL, especially when combined with coated tools, further reducing it. This indicates that the surface characteristics of the tool also have an impact on the formation and diffusion of oil mist. In conclusion, if the goal is to control the air quality in the workshop and reduce inhalable particulate matter, dry cutting or CMQL processes should be prioritized. And when lubrication is necessary, MQL should be avoided as much as possible to reduce health risks and environmental loads.

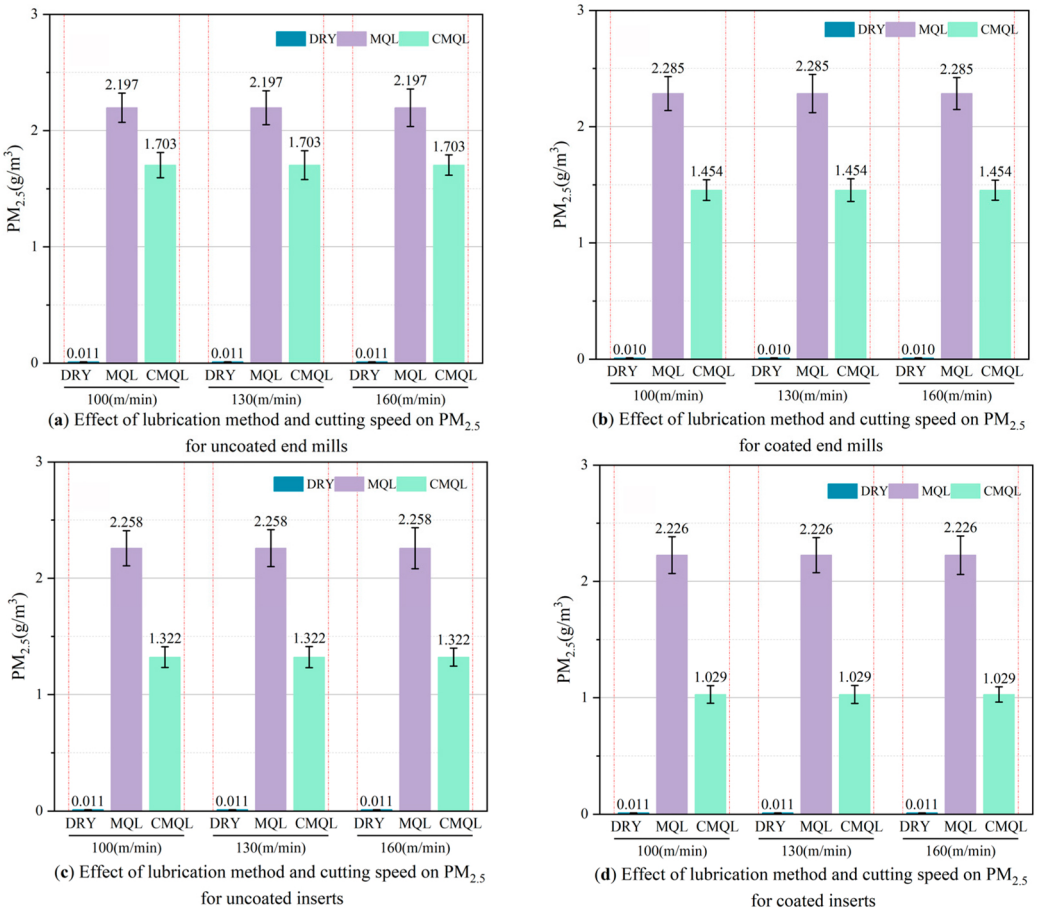


Figure 13. Effects of tool type, lubrication method, and cutting speed on the $PM_{2.5}$.

5.5. Results of Sensitivity Analysis

Based on the sensitivity analysis framework established in Section 3.4, this section systematically assesses the impact of the initial weight coefficient α and the minimum guarantee coefficient δ on the sustainability assessment results. The analysis covers 25 parameter combinations to comprehensively test the robustness of the model.

Figure 14 shows the ranking heat map of the benchmark optimal solution (coated blade—dry milling—160).

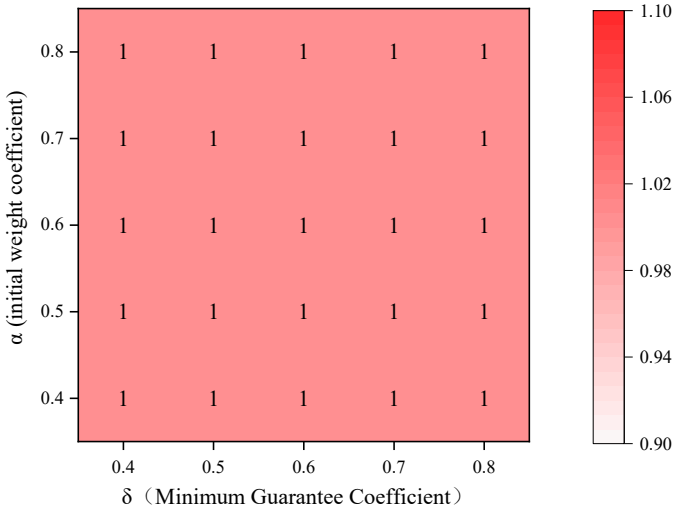


Figure 14. Ranking heatmap of the benchmark optimal solution across all (α, δ) parameter combinations.

From Figure 14, it can be seen that among all 25 parameter combinations, this solution ranks first 25 times, with a probability of remaining optimal at 100%. This finding validates the effectiveness of the analysis framework in Section 3.4, indicating that even when parameters vary over a wide range, the leading position of the optimal solution remains stable.

Figure 15 Heatmap of ranking stability, quantified as Spearman rank correlation coefficients between each alternative's ranking under varying (α, δ) parameter settings and its ranking in the benchmark case (α = 0.6, δ = 0.6). All coefficients exceed 0.954; the mean is 0.984—confirming exceptional robustness of the relative ranking order across the parametric space.

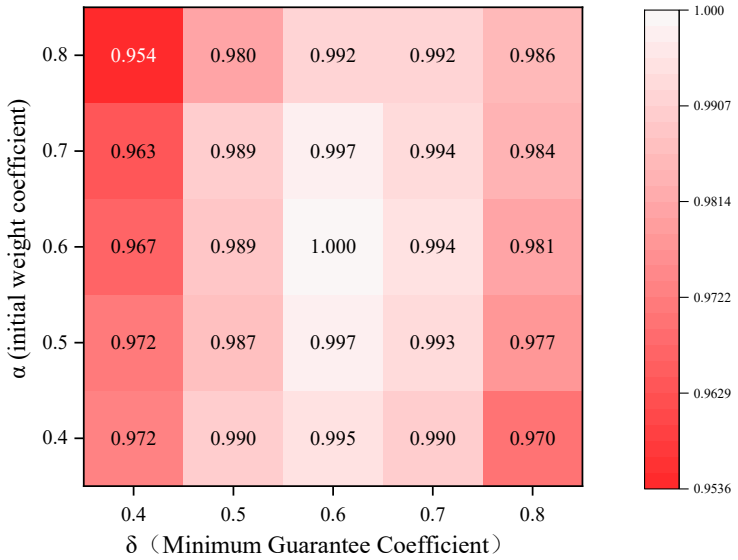


Figure 15. Heatmap of ranking stability across all (α, δ) parameter combinations.

5.6. Weight Allocation Based on Game Theory and Comprehensive Evaluation Results

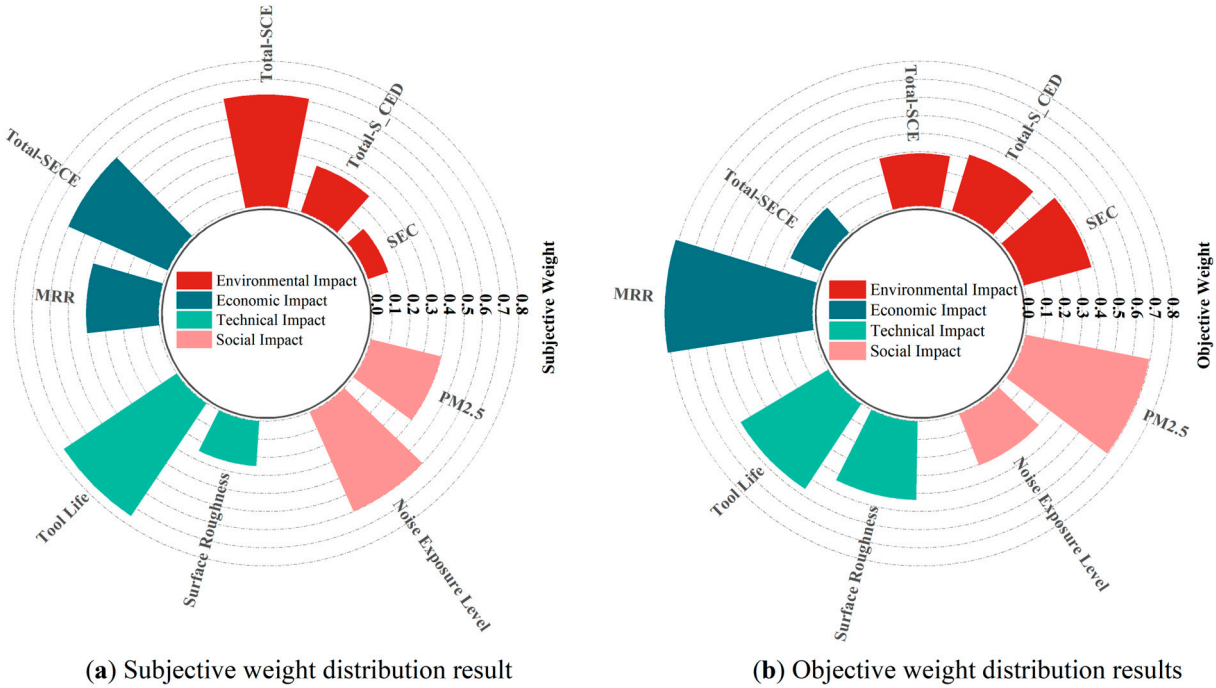
By integrating the experimental results with the weight allocation method described in Section 3, the criterion layer weights—representing the four sustainability dimensions—were determined through expert judgment. The resulting weight distribution is presented in Table 4.

Table 4. The weight distribution results for the criterion layer.

Criterion Layer	Environmental Impact	Economic Impact	Technical Impact	Social Impact
Weight	0.325	0.249	0.229	0.197

Figure 16 illustrates the subjective weight distribution derived from the AHP and the objective weight distribution obtained using the EWM. In Figure 16a, the subjective weighting results reveal a pronounced expert preference for environmental indicators at the life cycle level—specifically, Total-S_CED and Total-SCE—which are assigned higher weights, reflecting heightened concern for long-term energy consumption and carbon emissions under the "dual carbon" policy framework. High weights are also observed for MRR in the economic dimension and tool life in the technical dimension, highlighting the emphasis on production efficiency and machining stability. In contrast, Figure 16b shows that the objective weights are primarily driven by data variability, with MRR and $PM_{2.5}$ concentration receiving higher weights due to their significant variation across different process conditions, while environmental and technical indicators exhibit a more balanced

distribution. The divergence between subjective and objective weightings demonstrates that single-weighting methods cannot simultaneously capture decision-makers' preferences and intrinsic data patterns. This discrepancy further justifies the use of a game-theoretic approach in this study to integrate both types of weights, thereby enabling a more rational and balanced assessment of multi-dimensional sustainability objectives.



(**a**) Subjective weight distribution result (**b**) Objective weight distribution results

Figure 16. The distribution of subjective and objective weights.

The initial weights are derived from an integrated approach combining subjective and objective weighting methods, as illustrated in Figure 17.

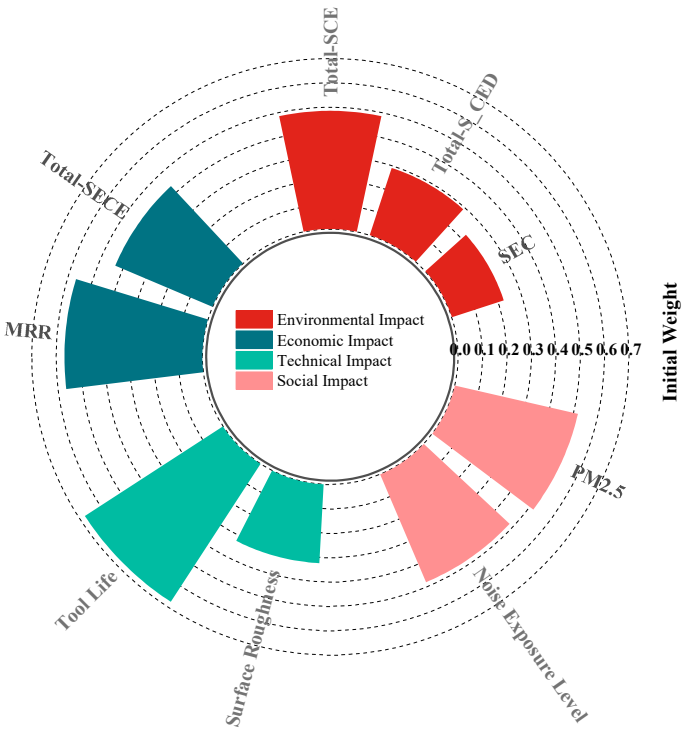


Figure 17. The initial weight allocation results.

Among them, key indicators such as "carbon emissions", "tool life", and "material removal rate" were assigned higher weights due to their significant roles in environmental impact, technical efficiency, and economic efficiency. However, this initial weighting is essentially a static weighted integration that fails to fully consider the goal conflicts and interest games among the four dimensions of environment, economy, technology, and society. Therefore, this paper introduces cooperative game theory, treating the four dimensions as "players" with different interest demands. Through the Nash bargaining model, a set of equilibrium weights are dynamically coordinated on the basis of ensuring the minimum weights of each dimension, combined with their policy bargaining power under the "dual carbon" goals, thereby enhancing the rationality and interpretability of the overall assessment.

After game-theoretic coordination, as illustrated in Figure 18, the final weights integrate both subjective and objective information while balancing the interests of multiple stakeholders. Notably, "carbon emissions" and "material removal rate" are assigned higher weights, reflecting a dual emphasis on low-carbon objectives and production efficiency. "Tool life" remains a key technical indicator, while the increased weight of "$PM_{2.5}$ concentration" underscores the growing importance of occupational health in decision-making.

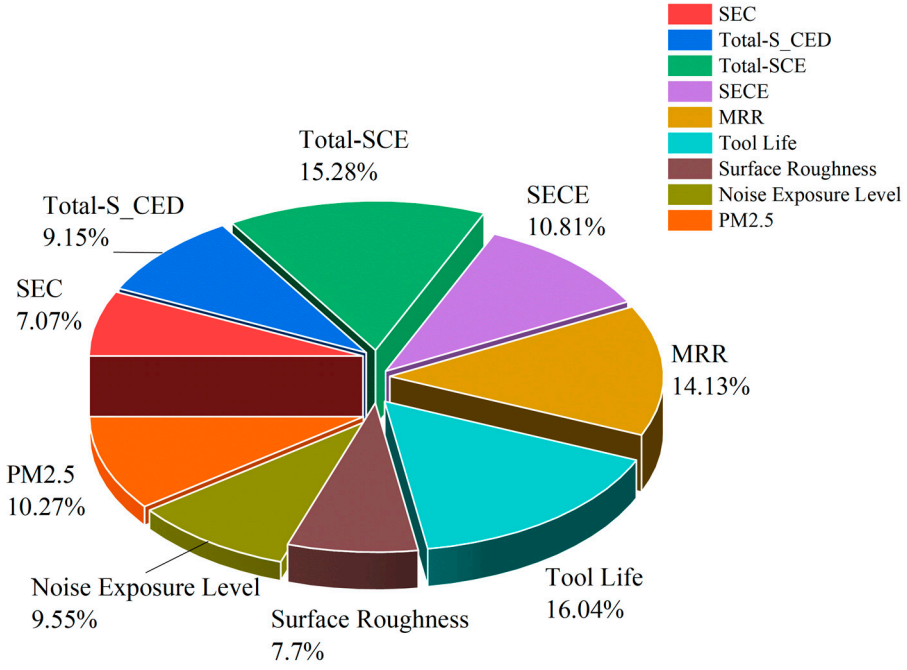


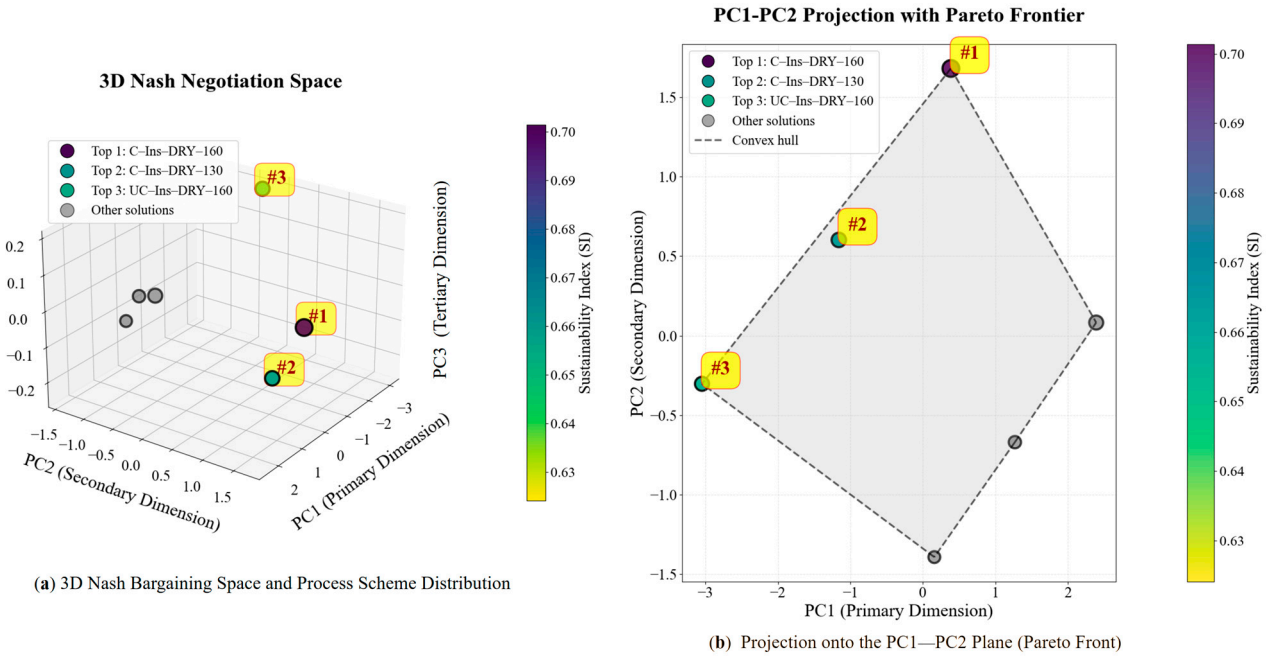
Figure 18. The final weight allocation results.

This weighting system, which integrates both subjective expertise from the Analytical Hierarchy Process and objective data-driven insights from the entropy weight method, and further reconciles multidimensional conflicts through a cooperative game-theoretic model, thus provides a realistic and balanced foundation for the subsequent calculation of the sustainability index. By coordinating the interests of environmental, economic, technical, and social dimensions based on the Nash equilibrium model, the final composite weights reflect a compromise acceptable to all stakeholders, thereby enhancing the rationality and interpretability of the evaluation. Using the derived weights and normalized experimental data, the sustainability index for each process plan was computed according to Equation 33. From the full set of 36 machining combinations, the process plans exhibiting superior sustainability performance were selected and ranked, with the top six configurations presented in Table 5.

Table 5. SI values of the top 6 process plans.

Ranking	Tool Type	Lubrication	Cutting Speed (m/min)	SI
1	Coated Insert	Dry	160	0.7014
2	Coated Insert	Dry	130	0.6613
3	Uncoated Insert	Dry	160	0.6552
4	Coated End Mill	CMQL	130	0.6550
5	Coated Insert	CMQL	160	0.6307
6	Coated End Mill	CMQL	160	0.6241

Based on the synergistic framework integrating Principal Component Analysis (PCA) and the Nash equilibrium Model [34], Figure 19 presents a visual analytical framework for a multidimensional sustainability decision space.



(**a**) 3D Nash Bargaining Space and Process Scheme Distribution

(**b**) Projection onto the PC1—PC2 Plane (Pareto Front)

Figure 19. Nash equilibrium space and Pareto frontier analysis for optimal sustainable process plans.

PCA was employed to reduce the dimensionality of high-dimensional evaluation indicators—encompassing environmental, economic, technical, and social dimensions—into three-dimensional and two-dimensional subspaces, thereby enabling a geometric representation of complex trade-off relationships. To enhance clarity and minimize visual clutter arising from the large number of process alternatives, only the three top-performing sustainable process plans identified in this study are displayed. In the three-dimensional negotiation space depicted in Figure 19a, each process plan is represented as a discrete data point, with its spatial coordinates reflecting the compromise state among competing objectives. A combined color and size gradient encodes the Sustainability Index (SI), effectively illustrating Pareto dominance across alternative solutions. Figure 19b further projects the data onto the PC1–PC2 plane, where the Pareto frontier is identified using a convex hull algorithm, thereby delineating the boundary of non-dominated solutions under current technological constraints. The Nash equilibrium point, representing the theoretical optimum derived through game-theoretic coordination, denotes an ideal solution in which stakeholder interests achieve a balanced compromise. Among all evaluated alternatives, the Coated Insert–Dry–160 plan demonstrates proximity closest to both the Nash equilibrium point and the Pareto frontier, indicating that its weight configuration

maximizes the Nash product within the equilibrium model. This reflects an optimal balance across environmental sustainability, economic efficiency, technical feasibility, and social acceptability. The proposed visualization approach not only validates the effectiveness of game-theoretic weight coordination but also provides a transparent and intuitive basis for multi-objective decision support in sustainable manufacturing.

Figure 20 compares nine indicators across four sustainability dimensions—environmental, economic, technical, and social—for coated end mills and coated inserts under three clean machining methods at a cutting speed of 130 m/min.



Figure 20. Radar chart comprehensive evaluation of three clean machining methods using coated end mill and coated insert (V_c = 130 m/min).

The data for each indicator were normalized and presented in radar charts to facilitate comparative analysis. All nine indicators are of the "smaller-is-better" type; for tool life and material removal rate, reciprocals were computed prior to normalization to ensure consistent directional alignment. Consequently, the overall performance under different clean machining methods can be evaluated by comparing the areas of their corresponding radar charts, where smaller areas indicate superior integrated performance. When machining with a coated end mill, CMQL exhibits distinct advantages, as evidenced by the smallest radar chart area, reflecting optimal overall performance across multiple criteria, including energy consumption, cost, tool life, surface quality, and environmental impact. It significantly outperforms both Dry and MQL, particularly in energy- and cost-related indicators such as Total-S_CED, Total-SCE, and Total-SCEC. However, regarding $PM_{2.5}$ emissions, although CMQL performs better than MQL, it remains considerably higher than Dry, indicating limitations in airborne particulate control that require further mitigation strategies (Figure 20a). In contrast, when using a coated insert, the Dry method yields the smallest radar chart area, indicating the most favorable overall performance, whereas CMQL results in the largest area and the poorest performance. Specifically, Dry significantly outperforms both MQL and CMQL in key energy efficiency and cost metrics, including SEC, Total-S_CED, Total-SCE, and Total-SCEC. Although CMQL demonstrates improved performance relative to MQL in terms of $PM_{2.5}$ emissions and noise reduction, it is markedly inferior to Dry on critical economic and energy-related indicators, resulting in a larger composite performance footprint. This suggests that the coated insert more effectively realizes its performance potential under dry machining conditions. Under CMQL, insufficient compatibility between the lubrication mechanism and the insert geometry may impede effective performance enhancement, thereby preventing the realization of the comprehensive benefits observed with coated end mills (Figure 20b).

A comprehensive analysis of the sustainability index (SI) for different lubrication methods and tool types (Figure 21) yields the following conclusions.

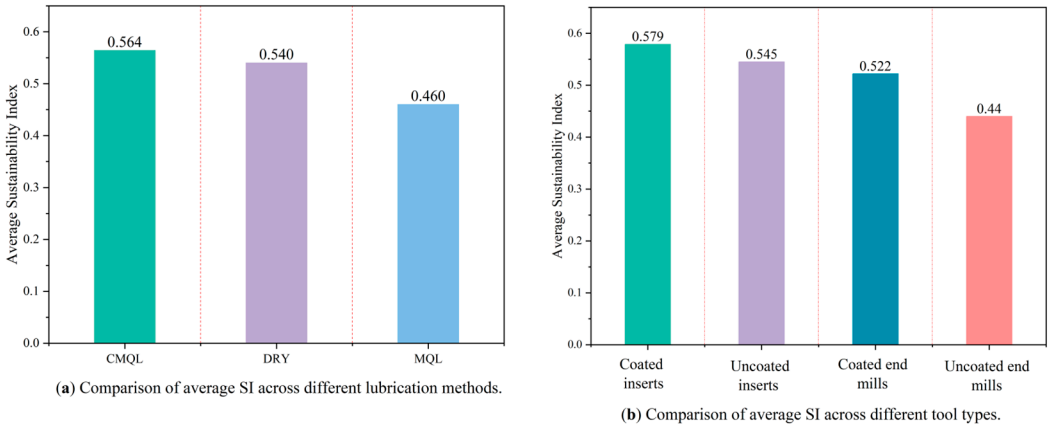


Figure 21. Comparison of average sustainability index (SI) across different lubrication methods and tool types.

As shown in Figure 21a, with respect to lubrication methods, CMQL demonstrates superior performance due to the synergistic effects of low-temperature cooling and micro-lubrication, delivering excellent outcomes in key indicators such as tool life, energy consumption control, and surface quality. It achieves the highest average SI value and exhibits the best overall sustainability. DRY offers advantages in environmental and economic dimensions but is hindered by rapid tool wear; MQL performs the poorest overall due to insufficient cooling and oil mist emissions. As illustrated in Figure 21b, regarding tool types, blade-type tools—particularly coated blades—benefit from low per-edge cost, reduced energy consumption, and ease of replacement enabled by their indexable design, outperforming face mills in life cycle carbon emissions, economic efficiency, and overall performance, thereby demonstrating greater sustainability potential. Coated tools consistently outperform their uncoated counterparts. In conclusion, the integration of CMQL with blade-type tools, especially coated blades, represents an optimal and more sustainable machining process configuration.

6. Conclusions

This study proposes a game theory–integrated framework for sustainability assessment of clean cutting technologies, incorporating environmental, technical, economic, and social dimensions. Subjective and objective weights were determined using AHP and EWM, respectively, and a cooperative game model was applied to balance multi-stakeholder interests through Nash equilibrium, enhancing the practicality and acceptability of the evaluation.

Key findings demonstrate that insert-type tools yield higher Sustainability Index (SI) values under dry milling due to their lower cost and operational efficiency. CMQL demonstrates superior overall sustainability across most scenarios, excelling in energy consumption control, tool life extension, and surface quality improvement—consistent with findings in reference [35]. Coated inserts also exhibit greater sustainability potential than end mills in terms of lifecycle energy use, carbon emissions, and economic performance. Additionally, cutting parameters and tool–lubrication compatibility significantly influence sustainability outcomes.

Several limitations should be acknowledged. The environmental assessment is conducted at the process level, and upstream infrastructure impacts associated with cryogenic CO_2 production and logistics are not explicitly included. In addition, the social sustain-

ability dimension is represented by a limited set of measurable indicators and does not fully capture all occupational safety risks related to cryogenic media handling. Future work will therefore focus on extending the proposed framework to broader manufacturing contexts and developing adaptive decision-support systems that incorporate expanded system boundaries and real-time sustainability optimization.

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