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## Article

# Proposal of a Combined AHP-PROMETHEE Decision Support Tool for Selecting Sustainable Machining Process Based on Toolpath Strategy and Manufacturing Parameters

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**Abstract:** Sustainable manufacturing technologies are the new challenge faced by enterprises, industries, and researchers. The development of a sustainability-based assessment method considering the environmental and economic impacts is crucial to realize viable manufacturing. However, few studies have addressed environmental economics and social flows using a common perspective. Mechanical machining is one of the most-used manufacturing techniques. The overall ecological, economic, and social footprint requires accurate and effective estimation and optimization. Several studies have addressed this issue by examining the entire process of machining, but sustainability flows for machining parameters and toolpaths have remained relatively unexplored. The lack of systematic assistance tools bridging the gap between decision-maker preferences and the three sustainability pillars—economic, social, and environmental—has impeded the widespread adoption of sustainable machining practices. To this end, this paper proposes an integrated approach to the decision-making problem that combines the Analytical Hierarchy Process (AHP) with the Preference Ranking Organization Method for Enrichment Evaluations (PROMETHEE) for selecting a sustainable machining strategy. The sustainability criteria are driven by manufacturing process parameters commonly employed and regulated during the manufacturing phase. This includes toolpath strategies as a qualitative input factor and manufacturing parameters such as cutting speed, feed rate, depth of cut, and stepover as quantitative input factors, affirming the practical applicability of the method in industrial contexts. New fundamental methods are also presented for selecting the most efficient machining parameters and toolpaths according to the weights assigned to each ecological, social, and economic footprint by the decision-maker (the manufacturer or production manager). In this way, sustainable machining strategies in the manufacturing industry will be strengthened in integrity. In a case study of part-end milling, both manufacturing parameters and toolpath strategies are considered to establish sustainable feature-based machining decisions.

**Keywords:** sustainable machining; toolpath strategies; machining parameters; environmental impact; machining cost; AHP; PROMETHEE



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## 1. Introduction

Manufacturing remains dominated by machinery, accounting for 60–80% of production and 15% of the total costs in developed countries [1]. Optimum production has been the goal for decades. As a result of sustainable development thinking [2], sustainability intersects economic, ecological, and social issues. Sustainable manufacturing processes, also known as green manufacturing, are therefore essential for the manufacturing industry [3]. Green

processing economics have been problematic due to higher manufacturing costs [4]. Global energy consumption is projected to rise from 575 quadrillion British thermal units (Btus) in 2015 to 736 quadrillion Btus by 2040 based on data from the US Energy Information Administration. Additionally, world carbon dioxide emissions (CO<sub>2</sub>) are experiencing an annual growth of 0.6% [5]. A substantial amount of carbon dioxide is emitted by manufacturing activities, which account for 40% of global energy consumption [6,7]. To promote sustainable manufacturing, a growing number of studies have been conducted to develop systems and manufacturing strategies with a minimal environmental impact [8,9].

In manufacturing industries, machining (material removal processes, such as turning and milling) represents 99% of the environmental impacts [10–13]. The topic of green machining has recently received a great deal of research attention, and many publications have been published on the subject [14,15]. In this regard, cutting parameters and toolpaths are two major research areas that are usually optimized separately.

Pangestu et al. developed a multi-objective optimization model to determine the optimal cutting parameters for a multi-pass turning process, including the spindle speed, feed rate, cutting depth, and roughing passes [16]. To achieve sustainable manufacturing, the optimization model examines several key indicators such as energy consumption, carbon emissions, production time, and production costs. Xu et al. developed a smart reasoning system to estimate energy consumption during milling processes and optimize the cutting parameters [17]. Under a variety of wear conditions, this system is capable of accurately predicting the amount of energy consumed. Moreover, it can optimize the cutting parameters to reduce energy consumption, improve machine tool stability, and improve the overall machining efficiency. Tian et al. presented a study that focuses on integrated optimization that is both environmentally conscious and economically conscious [18]. They addressed the issue of process routes and cutting parameters in low-carbon manufacturing environments. To solve this optimization problem and determine the optimal processing sequences and cutting parameters for each feature, they proposed the multi-objective NSGA-II algorithm. Zhang et al. developed a new analytical energy consumption model and optimized the cutting parameters to reduce the energy consumption of the micro-milling process [19]. For the reduction in the energy footprint and production time associated with face milling, Chen et al. proposed a comprehensive approach that involves optimizing the cutting tools and cutting parameters simultaneously [20]. In their study, it was demonstrated that optimizing the cutting parameters and the cutting tool can save more energy than either optimizing the parameters or optimizing the tool alone. A similar study was investigated by Shi et al. to assess the impact of the spindle rotation speed and cutting power on energy consumption in the end milling process [21]. Yin et al. proposed a method for selecting cutting parameters that consider both the cost and carbon emissions [22]. Optimization variables include the spindle speed, feed rate, and cutting depth, while constraints include the carbon emissions and processing costs. Tin et al. quantified relationships among the cutting parameters, tool wear, and production indexes, including the cost, CO<sub>2</sub> emissions, and time. A multi-objective optimization model was developed and then solved using a modified non-dominated sorting genetic algorithm (NSGA-II) [23].

A robust toolpath strategies optimization method remains a research gap to be addressed. The toolpath has always been the weak link in a machining process chain, although toolpath optimization can improve the performance by three times. Typically, toolpath optimization studies have been aimed at improving machined surfaces and machining efficiency [24–27]. For the last few decades, the impact of toolpaths on energy consumption has increasingly become the focus of researchers. Vila et al. conducted experimental investigations on the influence of cutting strategies and conditions during face milling operations on power consumption [28]. The manufacturing parameters were evaluated concerning the CO<sub>2</sub> emissions and surface roughness factors. Uzun et al. investigated the influence of toolpath strategies on the machining time, tool wear, and surface roughness during milling [27]. Pavanaskar and McMains conducted controlled machining experiments to analyze the impact of toolpath parameters on energy consumption [29]. An

analytical energy consumption model for CNC machining was established, integrating geometric toolpath parameters and machine construction effects into energy estimates. Altıntaş et al. developed a predictive model for the energy consumption of prismatic parts during milling considering the effects of different toolpaths [7]. Edem et al. [30] proposed a novel approach to determine the most energy-efficient toolpath strategy in mechanical machining using hyperMILL CAM software. They found that the feed axis energy demand in the  $y$ -axis direction was higher than the  $x$ -axis by 29, 19, and 11% for the zag, zigzag, and rectangular contour toolpaths, respectively. Edem and Mativenga [31] developed a scientific base and logic to calculate the energy consumption of a CNC toolpath taking the NC code as the input. In another study, Edem and Balogun presented an approach to analytically determine the most energy-efficient toolpath strategy in mechanical machining by evaluating the electrical energy requirement of the NC codes generated for the zag, zigzag, and rectangular contour toolpath strategies. Gao et al. [32] addressed the issue of considerable high electrical energy consumption associated with multi-axis end milling, which is frequently used for the machining of free-form surfaces. The discrete energy consumption path model is used to determine the shortest toolpath to find the optimal solution to the global energy consumption model.

In several research studies presented previously, energy reduction has been achieved by either optimizing the machining parameters or the tool trajectory. This limitation stems from the inability of conventional optimization methods to seamlessly integrate quantitative and qualitative variables simultaneously. Achieving a sustainable feature-based machining process necessitates the concurrent optimization of these two factors. Additionally, the extensive input data within CAM software present a challenge for process planners, leaving them undecided amid numerous choices. A decision support system (DSS) is needed for seamless integration into the digital mock-up (DMU), facilitating a data exchange with Life Cycle Assessment (LCA) tools and CAM software. The essential question is how to select the optimal combination of machining parameters and strategies to provide the most sustainable solution. A shift towards a multi-criteria perspective in sustainable development is a significant development, not only in industrial terms but also from a scientific perspective. This transition involves moving away from single-goal optimization towards considering multiple goals and criteria. Multi-criteria decision-making, which incorporates qualitative criteria alongside quantitative goals, offers versatile applications in this context [33,34].

In this paper, two multi-criteria decision-making methods are appropriately employed. Also, the concept of a DSS is adopted to facilitate sustainable decisions in machining. The main DSS components are data, a model base, and a user interface for interaction with humans [35]. As regards the existing DSSs for machining applications, most researchers focus on the selection of the machining process, machine tools, or machining parameters. Temuçin et al. proposed a DSS for selecting the suitable non-traditional machining process option for cutting operations on a specific material [36]. Taha and Rostam developed a fuzzy Analytical Hierarchy Process (AHP) integrated with a Preference Ranking Organization Method for Enrichment Evaluations (PROMETHEE) for a hybrid DSS [37]. The DSS enables the selection of the most suitable CNC machine among commercialized alternatives [34]. Niamat et al. [38] and Ming et al. [39] used multi-objective optimization to optimize electro-discharge machining process parameters. Shin et al. [40] and Khan et al. [41] both consider the sustainability criteria for the optimization of energy resources used during the machining process.

The crucial aspect is determining the optimal method for a specific issue, in light of the wide variety of techniques available, such as AHP [42,43], Élimination Et Choix Traduisant la Réalité (ELECTRE) [44], the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) [44,45], and PROMETHEE [46]. In the exploration of the criteria for assigning weights to computational methods, the AHP stands out as the primary technique for establishing these weights through pairwise comparisons. This is one of the strengths of our proposed methodology. Indeed, the decision-maker has the ability

to customize their preferences, assigning more value to one criterion over another. For instance, if they choose to prioritize the economic aspect over the social one, it will be reflected in the ranking of the machining strategy scenarios. Furthermore, the objectives of the study and the intricacies of the decision-making process influence the AHP's assessment of different criteria by dissecting them into a hierarchical framework. This, in turn, minimizes cognitive errors and potentially validates the decision-maker's consistency in establishing priorities. The well-acknowledged methods of multi-criteria decision-making (MCDM), when integrated with the AHP, encompass various methodologies, including AHP-TOSIS [47,48], AHP-VIKOR [49], AHP-Fuzzy Complex proportional assessment (CO-PRAS) [50], AHP-Criteria importance through inter-criteria correlation (CRITIC) [51], and Fuzzy AHP-PROMETHEE [37]. However, the PROMETHEE approach is considered relatively uncomplicated in both computation and conceptualization in contrast to alternative MCDM techniques. Despite being a versatile and efficient method capable of handling both quantitative and qualitative data, including group-level decisions, PROMETHEE possesses the potential to address complex problems with enhanced accuracy [33]. Crucially, the integrated approach of the AHP and PROMETHEE methodologies effectively addresses the complex decision-making processes and challenges related to the prioritization of alternatives. However, the prior literature highlights a distinct lack of utilization of the hybrid AHP-PROMETHEE modeling approach in assessing and ranking machining strategy scenarios concerning environmental performance, economic costs, and social considerations.

This study is motivated by the goal of devising a comprehensive assessment and ranking methodology that encompasses the diverse dimensions of sustainability performance within machining strategies. While the fusion of the AHP and PROMETHEE has been applied in diverse fields, this study contributes to the existing literature in the following ways:

- (1) Introducing an innovative application of the hybrid AHP-PROMETHEE approach specifically tailored for the assessment of machining strategy performance.
- (2) Providing a systematic methodology for integrating expert preferences to enhance the suitability of solutions.
- (3) Addressing the data requirement challenge by directly generating various combinations of machining parameters and strategies (i.e., alternatives for analysis) through the application of the Taguchi method. Additionally, the evaluation outcomes are derived from the integration of CAD/CAM/LCA systems.

The rest of this paper follows this structure: Section 2 delineates the methodologies applied in this study. Section 3 elucidates the findings and initiates a discussion. Conclusions are derived in Section 4.

## 2. Proposed Methodology

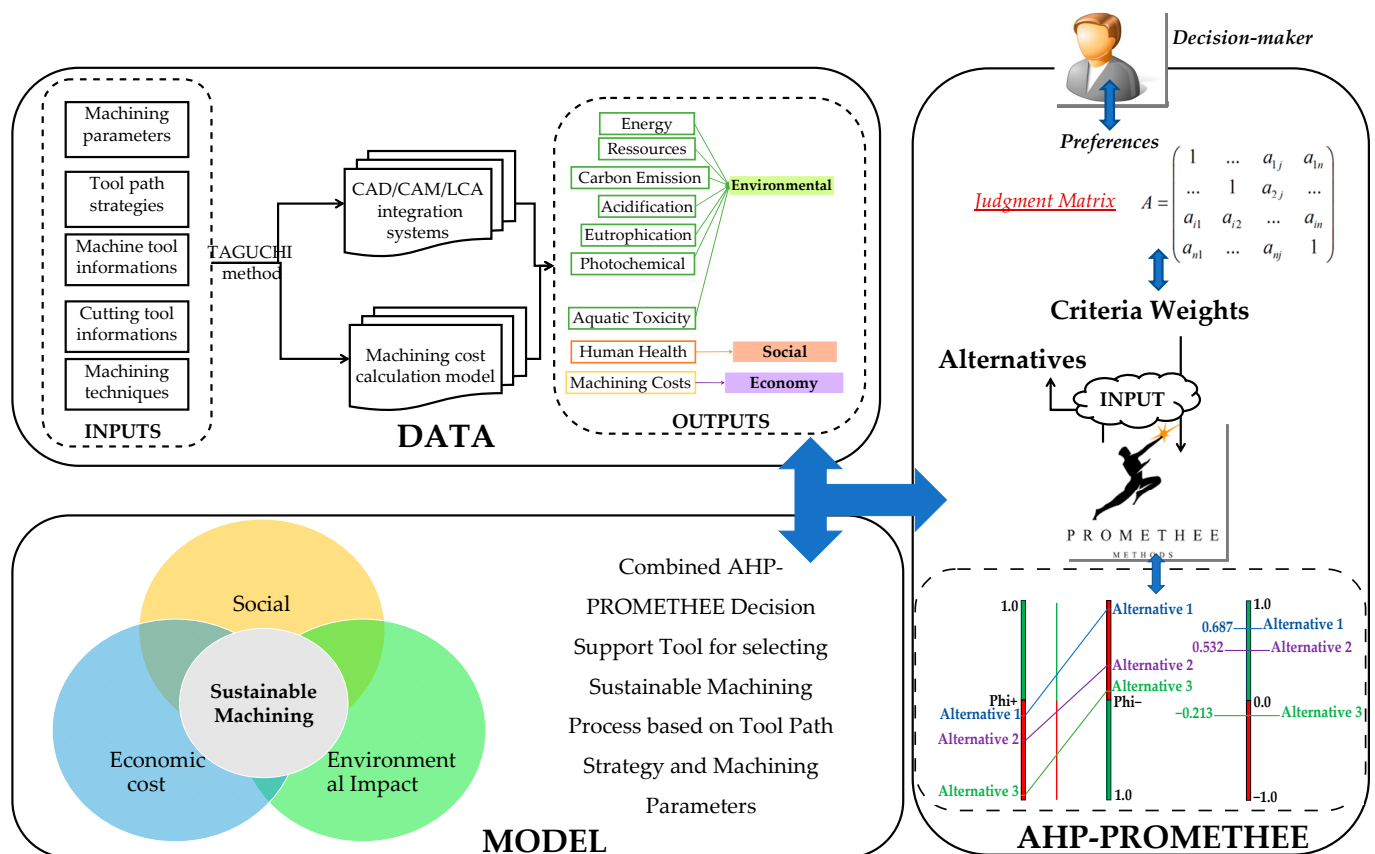
### 2.1. AHP-PROMETHEE Method-Based DSS

The proposed DSS includes three main components: (1) the data collected from a CAD/CAM/LCA system such as machining parameters, toolpath strategies, etc., (2) the user interface including the PROMETHEE Visual software (version 1.4.0.0, 2011–2013, Academic Edition) combined with the criteria weights provided by the decision-maker, and (3) the model consisting of the combined AHP-PROMETHEE approach (Figure 1).

AHP serves as a straightforward method for formulating and examining decisions [52]. Originated by Saaty [53], the AHP proves effective in addressing problems related to prioritizing alternative solutions. Apart from its broad applicability, the AHP facilitates the modeling and organization of intricate decision problems, assisting in the assignment of weights to criteria. The hierarchical decision tree is pivotal, breaking down complex problems into manageable subproblems, and providing decision-makers with a profound understanding of intricate relationships within the decision problem and the decision-making process. Furthermore, the eigenvector method is employed to calculate the criteria weights, ensuring higher levels of coherence, consistency, correlation, and accuracy com-



pared to intuition or domain knowledge-based weights [54]. Despite these advantages, the AHP does pose drawbacks in real-world decision problems, demanding a considerable number of pairwise comparisons, especially when dealing with a large number of criteria and/or alternatives. Consequently, this requirement transforms the preference elicitation stage into a cumbersome and time-consuming process. For these reasons, the AHP has been supplemented with PROMETHEE, offering decision-makers a more reliable evaluation and analysis.



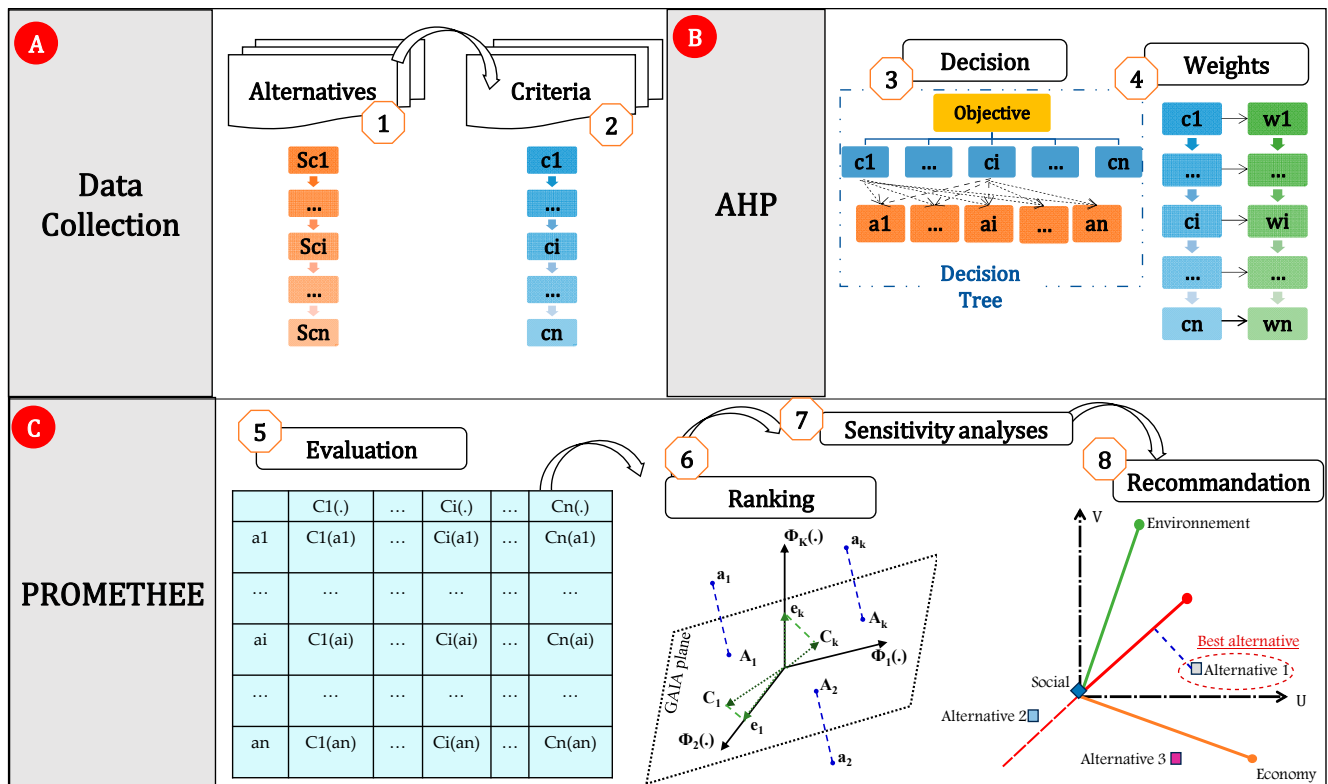
**Figure 1.** Overview of the proposed decision support system.

A major advantage of the PROMETHEE method is that it eliminates trade-offs between criteria scores and performs a direct synthesis, requiring evaluations of each alternative on each criterion. However, PROMETHEE has some limitations, namely a lack of guiding principles for structuring decision problems and determining criterion weights. Decision-makers may not always be able to judiciously evaluate criteria, which may not always be guaranteed in practice, making it difficult to understand complex decision problems that involve multiple levels of criteria and numerous alternative solutions.

The drawbacks outlined for PROMETHEE align with the strengths of the AHP method. Thus, these limitations of PROMETHEE can be circumvented by incorporating it with the AHP method, a concept we will elaborate on in the ensuing section.

## 2.2. Integrated AHP-PROMETHEE Approach

The combined AHP-PROMETHEE approach consists of three steps (Figure 2): (A) data collection, (B) application of the AHP, and (C) application of PROMETHEE.



**Figure 2.** The combined AHP-PROMETHEE approach.

### 2.2.1. Data Collection

The initial stage involves identifying the alternatives for evaluation and the primary objectives outlined by decision-makers, which must subsequently be translated into criteria.

Firstly, the alternatives subject to evaluation are identified as the machining scenarios for a given feature (step 1 in Figure 2). Using the Taguchi method, we will create a digital experimental plan based on the data and machining strategies that CAM software can provide to the manufacturer. Following this, for step 2, the primary objectives of decision-makers are defined and translated into criteria against which the alternative solutions will be assessed. In our case, the criteria for evaluation are the three pillars of sustainability: the environmental, social, and economic aspects. For the environmental aspect, we assess seven environmental impacts. These include energy consumption, resource consumption, greenhouse gas emissions contributing to the greenhouse effect (carbon emissions), acidification, eutrophication affecting air, water, and soil, photochemical pollution, and aquatic ecotoxicity. Regarding the social aspect, our methodology allows for the estimation of human health as an impact on society, which refers to the potential harm or adverse effects that certain substances or chemicals can have on human health. It encompasses a wide range of impacts, including acute and chronic effects. Finally, we consider machining costs as an economic criterion to be evaluated.

### 2.2.2. AHP

The application of the AHP involves initially gathering the information from steps 1 and 2, which will be used to construct a hierarchical decision tree (step 3). The hierarchical tree in analytics helps to visually represent the various criteria and alternatives in a structured and organized manner. It helps in breaking down a complex decision problem into a hierarchy of criteria and sub-criteria, making it easier to evaluate and compare different options. The hierarchical tree provides a clear framework for decision-makers to assess the relative importance of criteria and their corresponding alternatives, ultimately leading to a more informed and rational decision-making process. To express a preference for the

different criteria, weights are assigned in step 4 (Figure 3). To facilitate the input of the weight data, a graphical user interface is developed through Visual Basic for Applications programming. A comparison of elements in pairs will be made based on a standardized comparison scale of nine levels, reflecting the preferences of decision-makers between different options to determine the relative weighting for each criterion. The sub-criteria of the environmental, economic, and social criteria are compared two by two based on the desired objective to establish their respective importance, expressed in the form of a matrix called a judgment matrix (Equation (1)).  $n$  represents the total number of sub-criteria.

$$A = \begin{pmatrix} 1 & \dots & a_{1j} & a_{1n} \\ \dots & 1 & a_{2j} & \dots \\ a_{i1} & a_{i2} & \dots & a_{in} \\ a_{n1} & \dots & a_{nj} & 1 \end{pmatrix} \quad (i, j = 1, 2, \dots, n) \tag{1}$$

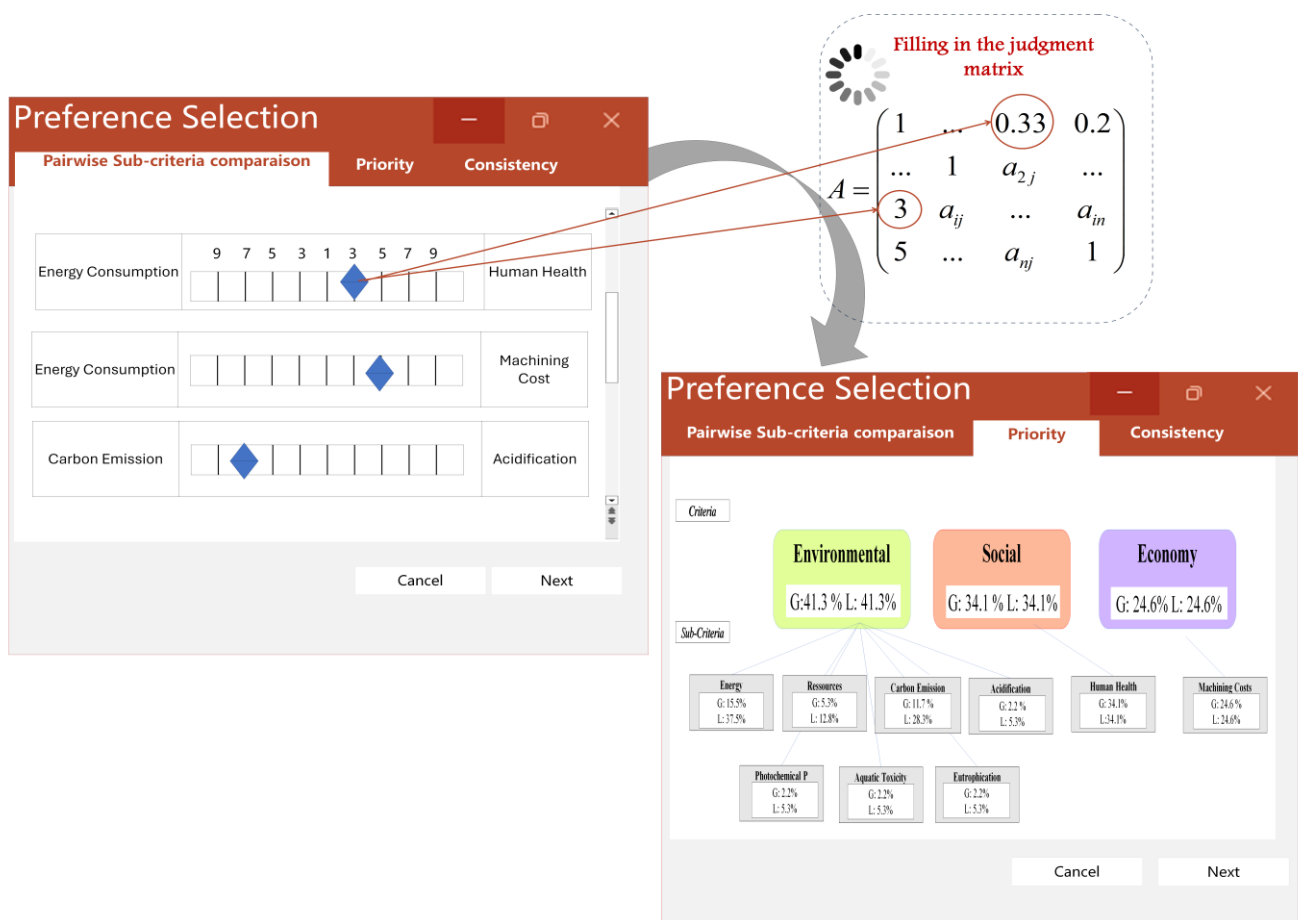


Figure 3. AHP application.

According to Equation (2), the right eigenvector  $w$  and the greatest eigenvector  $\lambda_{max}$  determine the relative priority  $Aw$ .

$$Aw = \lambda_{max}w \tag{2}$$

Pairwise comparisons are simple, intuitive, and practical means of extracting subjective information from the decision-maker. However, they can lead to inconsistencies in judgments. Therefore, to ensure consistent judgments in terms of proportionality and reliability, a consistency check is performed to assess the degree of coherence of the decision-maker judgments, which have been provided in the form of pairwise comparisons. This



is achieved by calculating the consistency ratio ( $Cr$ ) (Equation (3)).  $RI$  represents the random index and is calculated for matrices of different sizes, as shown in Table 1.  $CI$  is the consistency index. The  $Cr$  should not exceed 10%; otherwise, a review of judgments will be conducted to avoid or at least reduce inconsistencies. If the  $Cr$  is less than 10%, the judgment is considered acceptable, and the study can proceed.

$$Cr = \frac{CI}{RI}, \text{ such as } CI = \frac{\lambda_{max} - n}{n - 1} \quad (3)$$

**Table 1.** Consistency indices for a randomly generated matrix.

n	3	4	5	6	7	8	9	10
RI	0.58	0.9	1.12	1.24	1.32	1.41	1.45	1.49

### 2.2.3. PROMETHEE

Moving on to PROMETHEE, the evaluation table is constructed in step 5. To implement the PROMETHEE method, we will use the “Visual PROMETHEE” software, which requires the initialization of certain parameters: the alternatives to be ranked, the type of optimization (max/min), and the weights of the decision elements. Of course, the alternatives to be ranked are the machining scenarios, which are the combinations of different possible machining strategies and parameters determined from the Taguchi method in the first step. The input data consist of the environmental, economic, and social impacts resulting from each of the possible scenarios. The environmental and social assessment will be carried out using the integrations of the CAD/CAM/LCA integration systems. Subsequently, the weights of the decision elements are the priority of the criteria calculated by applying the AHP method. Finally, the software also asks us to determine the type of optimization, i.e., whether the criterion will be maximized or minimized during the evaluation. In our case, the goal is to minimize the generated impacts, which is why we will choose the “min” type for all assigned criteria. Figure 4 represents the modeling of our decision-making problem and the various assigned input data. Then, the alternatives are evaluated and ranked using a partial ranking with PROMETHEE I and a complete ranking with PROMETHEE II (step 6). PROMETHEE I is a multi-criteria decision analysis method used to rank and prioritize alternatives based on their performance against various criteria. It employs a pairwise comparison approach where decision-makers assess the relative importance or preference for one alternative over another concerning each criterion. The PROMETHEE I computes a preference index for each alternative, which reflects its overall desirability in comparison to the others. The higher the preference index, the better the alternative’s ranking. PROMETHEE II, on the other hand, is an extension of PROMETHEE I, introducing a preference function that quantifies the difference in performance between alternatives. This method not only considers the relative preferences for each criterion but also incorporates an aggregation function that accounts for interactions between criteria. PROMETHEE II offers a more sophisticated approach to decision-making, considering the interdependencies and synergies among criteria when ranking alternatives. In Section 4, these two methods were used to evaluate and rank the alternatives or options under consideration. PROMETHEE I provided a ranking based on the relative preferences for each criterion, while PROMETHEE II delved deeper into the interactions and dependencies among criteria to derive a more comprehensive ranking. These rankings can help in identifying the most suitable alternatives or options based on the specified criteria and contribute to the decision-making process. Step 7 involves conducting sensitivity analyses to confirm the robustness of the results obtained. Based on the information from PROMETHEE I, II, GAIA, and the sensitivity analyses, recommendations towards the best compromise can be formulated (step 8).



Figure 4. The representation of the decision-making issue and the diverse allocated input information.

### 3. Case Study

Since more than 80% of all mechanical parts can be cut by pocket machining [55], tool-path optimization methods are more significant in pocket milling. Thus, a pocket operation is selected as a case study. In our experimental setup, we employed ASTM A36 Steel, a type of low-carbon steel, as the workpiece material. The illustrated part can be seen in Figure 5. Initially, the block possesses dimensions of 200 mm × 120 mm × 20 mm and features a straightforward geometric pocket: a rectangle measuring 150 mm × 70 mm × 10 mm, adorned with four fillets each with a radius of 20 mm, and a cut width of 1 mm. For this operation, we assumed that the pocket would be machined using a cylindrical tool with a diameter of 10 mm, equipped with two flutes, and engaged at 75%. The selected tool material for this operation was carbide. Subsequently, Solidworks® was employed to generate a variety of toolpaths [56].

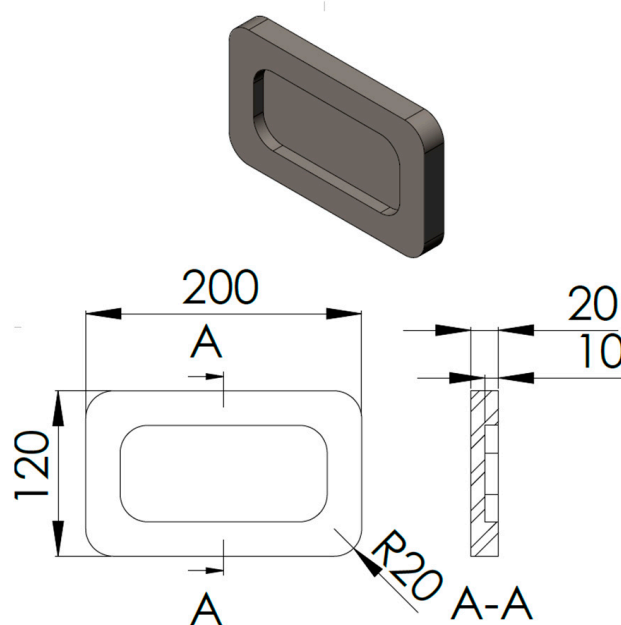


Figure 5. The case study part (modified from [56]).

To estimate the machining cost, these values have been sourced from the literature [56]. The labor rate for the operator is set at 28.320 Dinars (TND) per hour, while the machine rate for the machining center is assumed to be 14.160 Dinars per hour. Additionally, it is estimated that low-carbon steel is priced at approximately 5.390 Dinars per kilogram, and there is a factory expense of 2.270 Dinars for each part. The anticipated setup time per part is 1.2 min.

### 3.1. Step A: Data Collection

The PROMETHEE methodology necessitates a decision matrix that incorporates options along with their corresponding criterion evaluations. In the context of the presented scenario, the alternatives comprise four quantitative input parameters: cutting speed, feed rate, depth of cut, and stepover, alongside one qualitative parameter, which is the tool strategy. Consequently, the experimental setup was established based on five variable factors and four levels for each factor (as shown in Table 2). To streamline experiments yet maintain the ability to evaluate variable impact, a Taguchi fractional experimental design with 16 trials was employed, given the presence of 5 variables, each with 4 levels. The Taguchi method's experimental design is employed to systematically arrange the factors that influence the process, utilizing orthogonal arrays, which ensure a balanced design where factor levels carry equal weight. Table 2 represents the factors and levels of pocket milling [56].

**Table 2.** The values for the low, medium, and high levels for each parameter.

	Factors	Levels			
		1	2	3	4
Quantitative input factors	Cutting speed (m/min)	17	19	21	23
	Feed rate (mm/min)	120	180	240	300
	Depth of cut (mm)	0.2	0.4	0.6	0.8
	Stepover (mm)	2	3	4	5
Qualitative input factors	Toolpath strategy	Contour (C)	Zigzag (ZZ)	Zig (Z)	Spiral (S)

According to Taguchi's orthogonal array, a set of 16 experiments is a minimal set for this design of experiments (Table 3). Four levels were used since four toolpath strategies were studied: contour, zigzag, zig, and spiral.

**Table 3.** Experiments' factors (input) and results for 16 experiments defined by the Taguchi method.

Exp. No	Machining Strategy Level	Responses								
		Environmental Impacts							Cost (TND)	Human Health
		EI1 (MJ eq)	EI2 (kg Sb eq)	EI3 (kg CO <sub>2</sub> )	EI4 (kg SO <sub>2</sub> )	EI5 (kg PO <sub>4</sub> )	EI6 (kg 1.4-DB)	EI7 (kg 1.4-DB)		
1	C 1111	0.37000	0.00017	0.02576	0.00008	0.00005	0.00001	0.02628	30.9390	0.05852
2	ZZ1222	1.06201	0.00051	0.07396	0.00025	0.00015	0.00002	0.07545	29.7736	0.16802
3	Z1333	1.38662	0.00067	0.09657	0.00033	0.00020	0.00003	0.09851	20.7664	0.21938
4	S1444	2.12054	0.00102	0.14769	0.00050	0.00031	0.00004	0.15066	19.3702	0.33549
5	S2123	1.28148	0.00062	0.08925	0.00030	0.00019	0.00003	0.09104	50.7885	0.20274
6	Z2214	0.18901	0.00009	0.01316	0.00004	0.00003	0.00000	0.01343	13.0641	0.02990
7	ZZ2341	3.00000	0.00145	0.20892	0.00071	0.00044	0.00006	0.21312	31.3092	0.47458
8	C2432	1.81401	0.00087	0.12634	0.00043	0.00026	0.00004	0.12888	19.1302	0.28699

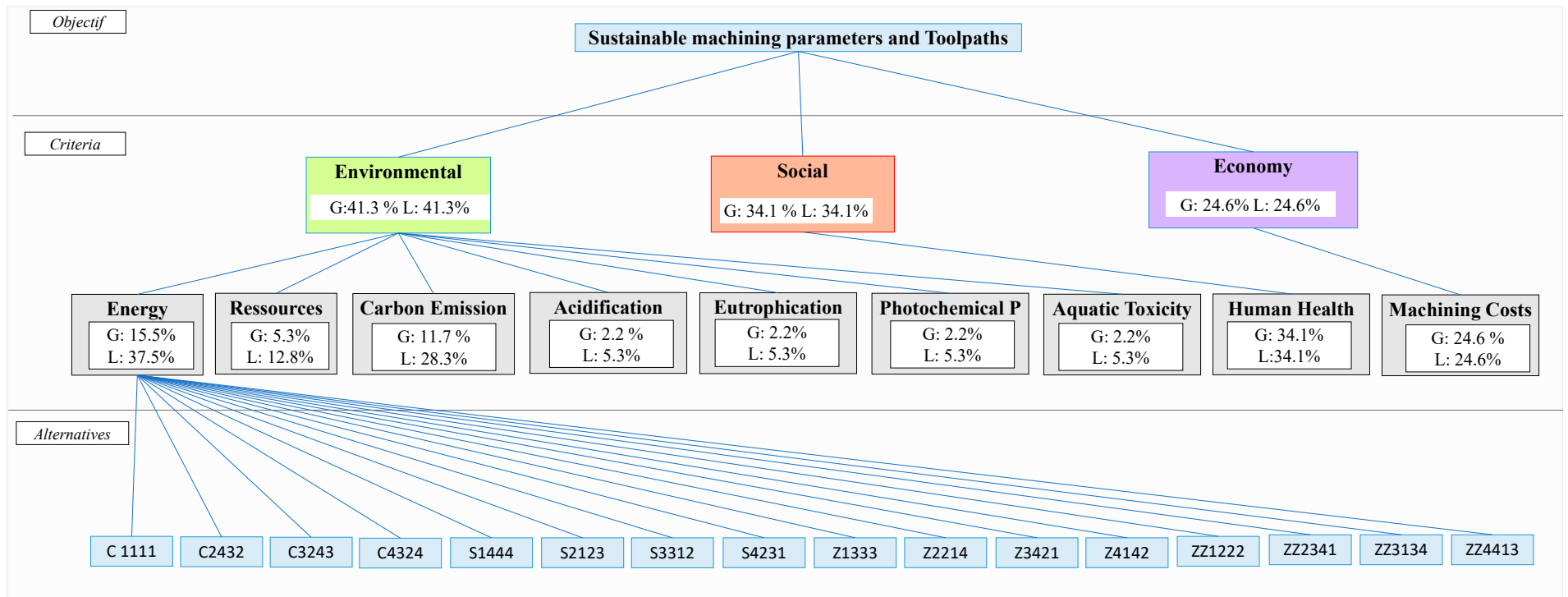
Table 3. Cont.

Exp. No	Machining Strategy Level	Responses								
		Environmental Impacts							Cost (TND)	Human Health
		EI1 (MJ eq)	EI2 (kg Sb eq)	EI3 (kg CO <sub>2</sub> )	EI4 (kg SO <sub>2</sub> )	EI5 (kg PO <sub>4</sub> )	EI6 (kg 1.4-DB)	EI7 (kg 1.4-DB)		
9	ZZ3134	1.05951	0.00051	0.07380	0.00025	0.00015	0.00002	0.07527	29.7127	0.16762
10	C3243	1.6996	0.00082	0.11838	0.00040	0.00025	0.00003	0.12075	24.5896	0.26889
11	S3312	0.42136	0.00020	0.02934	0.00010	0.00006	0.00001	0.02993	19.2697	0.06666
12	Z3421	1.70022	0.00082	0.11842	0.00040	0.00025	0.00003	0.12080	28.7505	0.26900
13	Z4142	2.2230	0.00107	0.15483	0.00053	0.00033	0.00005	0.15794	44.5595	0.35170
14	S4231	3.71351	0.00180	0.25864	0.00088	0.00055	0.00008	0.26384	64.3091	0.58752
15	C4324	0.69202	0.00033	0.04820	0.00016	0.00010	0.00001	0.04916	16.5085	0.10948
16	ZZ4413	0.21095	0.00010	0.01470	0.00005	0.00003	0.00000	0.01500	10.0133	0.03337

### 3.2. Step B: AHP

Based on the information collected previously, the hierarchical decision tree is constructed (Figure 6). In Figure 6, the illustration is limited to the scenarios of the energy sub-criteria. It highlights the different elements of our applied method: the objective, criteria (sustainability pillars), and sub-criteria on which the machining parameters and toolpaths will be evaluated in the next step. The proposed methodology offers the opportunity to the decision-maker to indicate their preference intensity for specific criteria. The process involves systematically evaluating and assigning preferences to individual criteria, specifically at a sub-criterial level of the sustainability criteria, through pairwise comparisons. This means that each criterion is compared with every other criterion, and a score is allocated to express the decision-maker's preference for one criterion over the other. The scoring is performed on a scale ranging from 1 to 9, where a score of 1 indicates equal importance, and a score of 9 signifies an extremely strong preference. This process enables a systematic assessment of the relative significance of each criterion within the decision-making framework, ultimately aiding in the determination of their respective weights or priorities. Equation (4) demonstrates the judgment matrix that is established according to the decision-maker's selected preferences. The resulting sub-criteria weights are 15.5% for energy consumption, 5.3% for resource utilization, 11.7% for greenhouse gas emissions, 2.2% for acidification, 2.2% for eutrophication, 2.2% for photochemical pollution, 2.2% for aquatic ecotoxicity, 34.1% for human health, and 24.6% for machining cost. The detailed result of the weight distribution is indicated in Figure 6. Environmental effectiveness emerged as the top priority, accounting for 41.3% of the overall preference. It was followed by social sustainability, which held a preference weight of 34.1%. Finally, the economic aspect was assigned a preference weight of 24.6%.

$$A = \begin{pmatrix} 1 & 5 & 3 & 7 & 7 & 7 & 7 & 0.33 & 0.2 \\ 0.2 & 1 & 0.33 & 3 & 3 & 3 & 3 & 0.14 & 0.14 \\ 0.33 & 3 & 1 & 7 & 7 & 7 & 7 & 0.2 & 0.2 \\ 0.14 & 0.33 & 0.14 & 1 & 1 & 1 & 1 & 0.11 & 0.11 \\ 0.14 & 0.33 & 0.14 & 1 & 1 & 1 & 1 & 0.11 & 0.11 \\ 0.14 & 0.33 & 0.14 & 1 & 1 & 1 & 1 & 0.11 & 0.11 \\ 0.14 & 0.33 & 0.14 & 1 & 1 & 1 & 1 & 0.11 & 0.11 \\ 3 & 7 & 5 & 9 & 9 & 9 & 9 & 1 & 7 \\ 5 & 7 & 5 & 9 & 9 & 9 & 9 & 0.14 & 1 \end{pmatrix} \quad (4)$$



**Figure 6.** The hierarchical decision tree and weight distribution; L indicates the local priority and G indicates the global priority of a specific criteria or sub-criteria.

To assess the consistency of the assessment, the consistency ratio ( $Cr$ ) is calculated using Equation (3). The  $Cr$  is equal to 7.38%. The analysis reveals that the consistency ratios of our case study are below 10%, affirming the consistency of our judgment matrix, and allowing us to proceed with our localized decision support. Ultimately, we will enhance the ranking scheme by employing the PROMETHEE method, utilizing the chosen standard judgment matrix and the priorities established through the AHP method.

### 3.3. Step C: PROMETHEE

After determining the weights of each impact index, an environmental, social, and economic assessment was progressively developed. Furthermore, the three sustainability pillars are measured based on an LCA software “Bilan Produit” (version 2011), developed by ADEME [57]. The database utilized was created in partnership with the EcoInvent Center and the Swiss Center for Life Cycle Inventories [58]. It was implemented using the Commitment Modeling Language (CML) method [59], and seven environmental impact indicators are determined: EI1 = energy consumption (MJ eq), EI2 = resource consumption (kg Sb eq), EI3 = greenhouse effect GWP 100 mod (carbon emission) (kg CO<sub>2</sub> eq), EI4 = acidification (kg SO<sub>2</sub> eq), EI5 = eutrophication (air water soil) (kg PO<sub>4</sub>—eq), EI6 = photochemical pollution (kg C<sub>2</sub>H<sub>4</sub>), and EI7 = aquatic ecotoxicity (kg 1,4-DB eq). For social sustainability, human health (kg 1,4-DB eq) is calculated, and we consider the machining costs as an economic criterion for assessment. All these data constitute the input for the PROMETHEE method. Based on decisions made by the decision-maker, this method will enable us to rank the various machining scenarios.

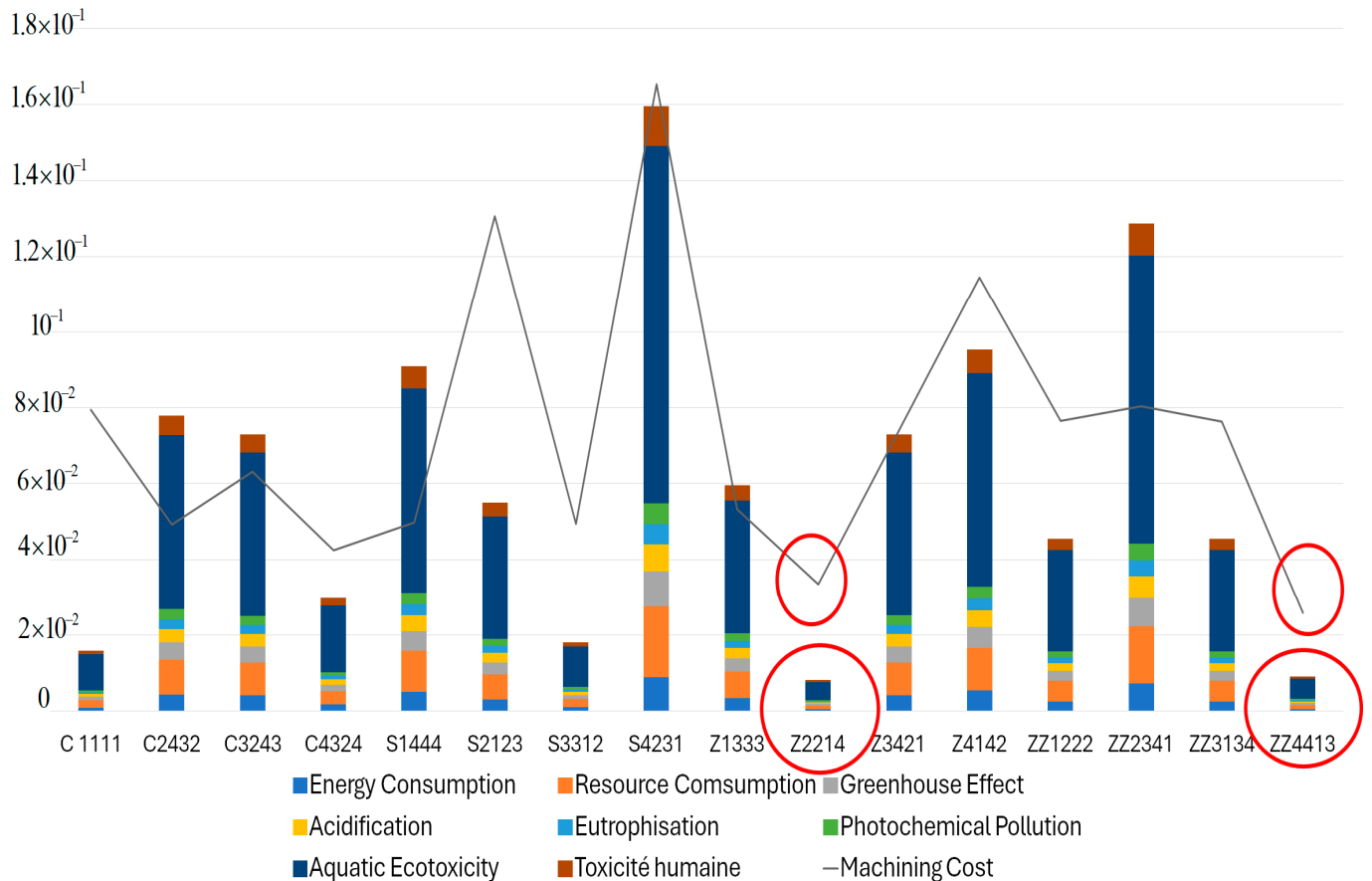
## 4. Results

Based on the CAD/CAM/LCA integrations, an assessment of the environmental, social, and economic impacts was conducted. Table 3 represents the results generated from the various proposed machining scenarios. The machining strategy level is encoded as follows: toolpath type (C/ZZ/Z/S), cutting speed level, feed rate level, depth of cut level, and width of cut level. For instance, the ZZ1222 machining strategy, corresponding to the experience no. 2), represents the cutting speed = 17 m/min, feed rate = 180 mm/min, depth of cut = 0.4 mm, stepover = 3 mm, and the toolpath is the zigzag type. These outcomes (Table 3) may be perplexing for a designer who is not an expert in sustainable development. Figure 7 provides a visual representation of the environmental, social, and economic performance distribution for each of the proposed machining strategies. Notably, the Z2214 and ZZ4413 strategies emerge as the top-performing options (highlighted by red circles in Figure 7). However, it is important to note that this assessment remains valid when the sustainability criteria carry equal weights, but its effectiveness diminishes when the criteria are assigned differing weights. This means that the comparison holds when all sustainability pillars have equal importance, but its applicability becomes limited when certain pillars are considered more significant than others in the decision-making process. Therefore, we turned to the PROMETHEE method to rank the machining scenarios.

At this stage, the PROMETHEE method is deployed to address the challenge of identifying the optimal combination of machining parameters that aligns most effectively with the weight distribution suggested by the decision-maker. So, the problem is constructed by 16 alternatives and 9 quantitative criteria. To implement the PROMETHEE method, we used the “Visual PROMETHEE” software, which necessitates the initialization of specific parameters. These parameters encompass the alternatives that need to be ranked, the optimization type (max/min), and the decision element weights. Figure 8 provides a visual representation of our decision problem modeling and the various input data associated with it. The alternatives to be ranked are the machining strategies generated through the Taguchi fractional design, which encompasses the combinations of the machining parameters. The input data include information about the environmental impacts, human health, and machining costs, all of which have been meticulously calculated and are provided in Table 3. Additionally, the decision element weights are derived from the priorities as-



signed to the criteria, which were determined using the AHP method. Lastly, the software prompts us to specify the type of optimization, that is, whether a given criterion should be maximized or minimized during the evaluation process. In our specific case, our objective is to maximize the sustainability performance. Therefore, we will opt for the “min” type for all the assigned criteria.



**Figure 7.** Comparison of no-weighted results from different machining scenarios.

The partial ranking by PROMETHEE I is presented in Figure 9a. Figure 9a showcases the performance of two alternatives, ZZ4413 and Z2214, which appear to be very closely ranked concerning the assessed criteria. This proximity in their rankings suggests a state of “indifference”, signifying the significant challenge faced by the decision-maker in establishing a clear and unequivocal preference between these two alternatives. Indeed, in simple scenarios, partial ranking by PROMETHEE I is often sufficient to address decision problems. However, in certain circumstances, partial ranking falls short due to challenges related to indifference or incommensurability. For instance, the overlapped and overlaid scenario ranking is highlighted by the red dashed circle in Figure 9a. It is for this reason that PROMETHEE II provides a comprehensive ranking, from the best alternative to the worst. Figure 9b illustrates a PROMETHEE II final ranking. The red dashed circle in Figure 9b illustrates the ranking improvement. As shown in Figure 9b, a specific alternative, ZZ4413, distinctly emerges as the optimal choice based on the assigned weights of the criteria. This scenario is defined by the cutting speed = 23 m/min, feed rate = 300 mm/min, depth of cut = 0.2 mm, stepover = 4 mm, and a zigzag toolpath. This machining strategy has outperformed the others across the various criteria, resulting in its superior ranking.

	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>
Scenario1	Energy	Resources	Carbon Emis...	Acidification	Eutrophication	Photochemic...	Aquatic Toxi...	Human Toxicity	Costs	
Unit	MJ	(10-3) kg Sb	Kg CO2	Kg SO2	Kg PO4	Kg1,4DB	Kg1,4DB	Kg 1,4 DB	Dinars	
Cluster/Group	●	●	●	●	●	●	●	◆	◆	
<b>Preferences</b>										
Min/Max	min	min	min	min	min	min	min	min	min	
Weight	16,63	2,00	13,30	0,33	0,33	0,33	0,33	36,81	29,92	
Preference Fn.	Linear	Linear	Linear	Linear	Linear	Linear	Linear	Linear	Linear	
Thresholds	absolute	absolute	absolute	absolute	absolute	absolute	absolute	absolute	absolute	
- Q: Indifference	1,00	1,00	1,00	1,00	1,00	1,00	1,00	1,00	1,00	
- P: Preference	2,00	2,00	2,00	2,00	2,00	2,00	2,00	2,00	2,00	
- S: Gaussian	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	
<b>Statistics</b>										
Minimum	0,19	0,90	0,01	0,40	0,30	0,00	0,01	0,03	10,01	
Maximum	3,71	18,00	0,26	8,80	5,50	8,00	0,26	0,59	64,31	
Average	1,44	6,91	0,10	3,38	2,09	2,88	0,12	0,23	28,30	
Standard Dev.	0,97	4,71	0,07	2,31	1,44	2,12	0,08	0,15	13,94	
<b>Evaluations</b>										
<input checked="" type="checkbox"/> C 1111	0,37	1,70	0,03	0,80	0,50	1,00	0,26	0,06	30,94	
<input checked="" type="checkbox"/> ZZ1222	1,06	5,10	0,07	2,50	1,50	2,00	0,08	0,17	29,77	
<input checked="" type="checkbox"/> Z1333	1,39	6,70	0,10	3,30	2,00	3,00	0,10	0,22	20,77	
<input checked="" type="checkbox"/> S1444	2,12	10,20	0,15	5,00	3,10	4,00	0,15	0,34	19,37	
<input checked="" type="checkbox"/> S2123	1,28	6,20	0,09	3,00	1,90	3,00	0,09	0,20	50,79	
<input checked="" type="checkbox"/> Z2214	0,19	0,90	0,01	0,40	0,30	0,00	0,01	0,03	13,06	
<input checked="" type="checkbox"/> ZZ2341	3,00	14,50	0,21	7,10	4,40	6,00	0,21	0,48	31,31	
<input checked="" type="checkbox"/> C2432	1,81	8,70	0,13	4,30	2,60	4,00	0,13	0,29	19,13	
<input checked="" type="checkbox"/> ZZ3134	1,06	5,10	0,07	2,50	1,50	2,00	0,08	0,17	29,71	
<input checked="" type="checkbox"/> C3243	1,70	8,20	0,12	4,00	2,50	3,00	0,12	0,27	24,59	
<input checked="" type="checkbox"/> S3312	0,42	2,00	0,03	1,00	0,60	1,00	0,03	0,07	19,27	
<input checked="" type="checkbox"/> Z3421	1,70	8,20	0,12	4,00	2,50	3,00	0,12	0,27	28,75	
<input checked="" type="checkbox"/> Z4142	2,22	10,70	0,15	5,30	3,30	5,00	0,16	0,35	44,56	
<input checked="" type="checkbox"/> S4231	3,71	18,00	0,26	8,80	5,50	8,00	0,26	0,59	64,31	
<input checked="" type="checkbox"/> C4324	0,70	3,30	0,05	1,60	1,00	1,00	0,05	0,11	16,51	
<input checked="" type="checkbox"/> ZZ4413	0,25	1,00	0,01	0,50	0,30	0,00	0,01	0,03	10,01	

Figure 8. Input matrix in Visual PROMETHEE Software.

In Figure 10, we gain valuable insights into the dynamics of the ranking results because of altering the assigned weights. The purpose is to identify the impacts of decision-maker preferences on the scenario ranking order. Figure 10a–c shows the resulting scenario ranking for different assigned weights. The significance of the environmental dimension is clearly exemplified when its weight is adjusted from 41% (Figure 10a) to 90% (Figure 10b). This notable shift in preference places greater emphasis on environmental considerations, and as a result, we witness a distinct transformation in the ranking of the different scenarios. Indeed, this weight modification yields Z2214 taking the lead, surpassing ZZ4413, which was previously the favored option.

These shifts underscore the responsiveness of the decision-making process to adjustments in the weight distribution, showcasing the ability of the PROMETHEE II method to adapt to evolving priorities. It serves as a compelling demonstration of the methodology’s utility in assisting decision-makers in fine-tuning their choices to align with their evolving criteria and objectives. The case study demonstrates the effectiveness of the proposed approach, which introduces an innovative and reliable DSS-based hybrid AHP-PROMETHEE approach for assessing and ensuring the sustainability performance of machining strategies. This study systematically integrates expert preferences and overcomes data challenges by generating various machining parameters and strategy combinations, aiming for seamless integration into the digital mock-up.

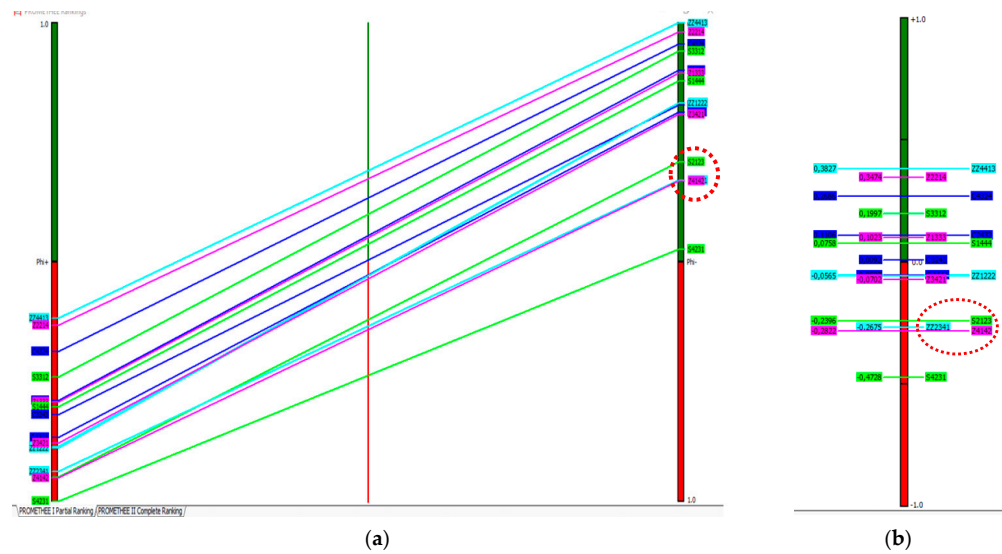


Figure 9. (a) PROMETHEE I partial ranking of alternatives; (b) PROMETHEE II complete ranking of alternatives.

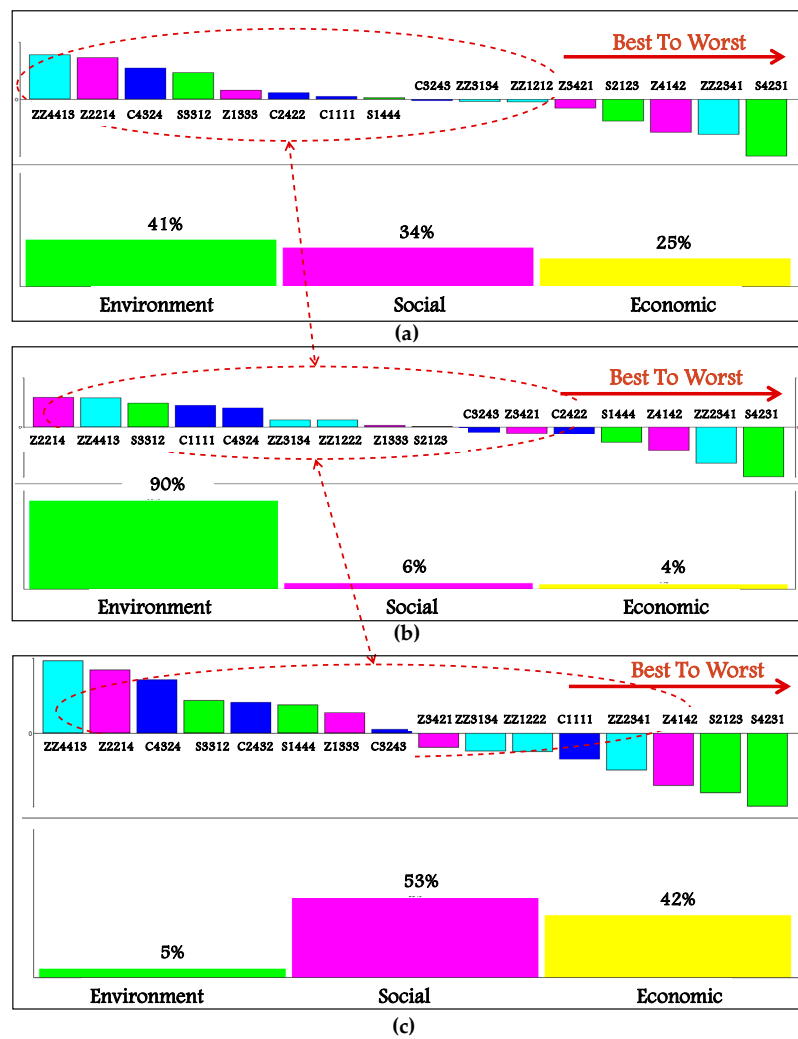


Figure 10. Influence of criteria weights on the choice of the most sustainable machining scenario: (a) assigned weights in case study, (b) Environment 90%, Social 6%, Economic 4%, (c) Environment 5%, Social 53%, Economic 42%.

## 5. Conclusions

The main aim of this study is to introduce a novel application of a hybrid multi-criteria decision-making (MCDM) model, specifically designed for evaluating machining strategies and parameters with a strong emphasis on sustainability considerations. This study is geared towards assisting manufacturers in selecting the most suitable scenario according to their preferences. To achieve this objective, this study effectively combines the strengths of both the AHP and PROMETHEE to establish a robust and all-encompassing MCDM methodology. Acknowledging that each of these methods has its unique advantages and limitations, this study strategically utilizes the AHP for structuring the decision-making problem and determining the weights of various criteria. The evaluation of the machining strategy scenarios, generated through the Taguchi method, revolves around three primary criteria groups: environmental, social, and economic factors. These criteria are further broken down into a total of nine sub-criteria, addressing aspects such as energy consumption, resource utilization, greenhouse gas emissions (specifically carbon emissions) contributing to the greenhouse effect, acidification, eutrophication affecting the air, water, and soil, photochemical pollution, and aquatic ecotoxicity, all of which are under the umbrella of environmental impacts. The social dimension is captured through human health, while economic considerations are evaluated through machining costs. Undoubtedly, the criteria weights are assigned based on the preferences of the decision-maker through the application of the AHP method. Subsequently, PROMETHEE is enlisted to aggregate these criteria, ranking different machining strategy scenarios, and conducting sensitivity analyses. In certain instances, the partial ranking of alternatives may remain inconclusive due to complexities arising from indifference or incomparability among the options. To address these intricacies, PROMETHEE II emerges as the solution, offering a comprehensive ranking of the alternatives. This ensures that every alternative is ranked from best to worst, eliminating any ambiguities in the decision-making process.

The case study involves the assessment of various machining strategy scenarios, which are determined by five input parameters. These parameters encompass four quantitative factors: cutting speed, feed rate, depth of cut, and stepover, along with one qualitative factor, which is the tool strategy. The experimental design is structured around 5 variables, each with 4 distinct levels, resulting in a total of 16 different alternatives. When applying the AHP, the preferences of the manufacturer were taken into account. Based on these preferences, the assessment criteria were prioritized. This hierarchy of preferences was instrumental in guiding the decision-making process within the case study. Utilizing the integration of CAD/CAM/LCA, an extensive evaluation was carried out to assess the environmental, social, and economic impacts associated with each machining strategy scenario. Subsequently, the PROMETHEE I and II methods were employed to tackle the challenge of identifying the most optimal combination of machining parameters, aligning with the weight distribution suggested by the decision-maker.

While this study employs a combined AHP-PROMETHEE approach to rank the machining strategy scenarios from a sustainability perspective, certain limitations have come to light. The primary limitation revolves around the subjective selection of the criteria. Consequently, future research endeavors should place special emphasis on addressing this concern, aiming to enhance the objectivity and robustness of the methodology. Furthermore, future research efforts should be directed towards the development of a dynamic meta-model that encompasses all the parameters involved in a machining operation. These parameters should include the choice of workpiece material, cutting fluid, cutting tool, and the machine tool utilized.

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