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Fuzzy Multi-Criteria Evaluation of In Situ Coal Pyrolysis for Sustainable Hydrogen Production

Alpaslan Atmanli [1,*], Burl Donaldson [2], Hakan Ayhan Dağıstanlı [3] and Nadir Yilmaz [4]

[1] Department of Mechanical Engineering, National Defense University, 06654 Ankara, Turkey
[2] Department of Mechanical Engineering, New Mexico State University, Las Cruces, NM 88003, USA; abdonalds@gmail.com
[3] Department of Industrial Engineering, National Defense University, 06654 Ankara, Turkey; hakanayhan.d@msu.edu.tr
[4] Department of Mechanical Engineering, Howard University, Washington, DC 20059, USA; nadir.yilmaz@howard.edu
* Correspondence: alpaslan.atmanli@msu.edu.tr; Tel.: +90-312-417-51-90

Abstract

The growing demand for hydrogen as a low-carbon energy carrier has renewed interest in coal, an abundant and globally available resource, making it crucial to assess its suitability for efficient hydrogen production via in situ pyrolysis. The main objective of this study is to propose a new and robust hesitant fuzzy Multi-Criteria Decision-Making (MCDM) framework to the literature to determine the coal alternative that will provide the most efficient hydrogen production. For this purpose, five different coals with the largest reserves in the United States (Wyoming, Illinois, West Virginia, Kentucky, and Pennsylvania) were examined under eight criteria. To manage uncertainties in determining the weights of the criteria, the hesitant fuzzy set-based step-wise weight assessment ratio analysis (SWARA) method was used. The coal alternatives were ranked using the Alternative Ranking Technique based on Adaptive Standardized Intervals (ARTASI). The proposed framework uses expert evaluations and performance criteria as input parameters to determine criterion weights and rank the alternatives. The output consists of the calculated criterion weights, utility values, and the final ranking of the liquid hydrogen rocket oxidizer systems. The robustness of the obtained results is further verified through parametric analyses of the w and Ψ parameters and comparative other MCDM methods validation. The findings consistently demonstrate that Wyoming coal is the most suitable alternative for hydrogen production via in situ pyrolysis. This study provides a systematic decision support framework for evaluating coal resources and offers valuable guidance for future hydrogen production strategies based on in situ coal pyrolysis.

Keywords: coal; hydrogen production; pyrolysis; in situ process; decision-making

Check for updates

Academic Editor: Dicho Stratiev

Received: 7 June 2026
Revised: 23 June 2026
Accepted: 25 June 2026
Published: 1 July 2026

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1. Introduction

Hydrogen is widely recognized as a key energy carrier for achieving global decarbonization targets and supporting the transition to sustainable energy systems [1,2]. Despite growing investments in renewable hydrogen pathways, coal remains a strategically important feedstock because of its extensive global reserves and capacity for large-scale hydrogen production [3,4]. Among coal conversion technologies, pyrolysis offers a viable route to generating hydrogen-rich gases while recovering valuable carbonaceous products [5]. In particular, in situ coal pyrolysis has attracted increasing

attention because it allows conversion to occur directly within underground coal seams, thereby reducing extraction-related impacts and potentially enhancing economic and environmental performance [6]. Because the effectiveness of in situ hydrogen production is strongly influenced by coal characteristics, identifying the most suitable coal resources has become a critical challenge, requiring systematic and comprehensive evaluation approaches [7,8].

Given the significant variations in geological, chemical, and physicochemical properties among coal resources, determining the most suitable coal alternative for hydrogen production through in situ pyrolysis represents a complex decision-making problem. Such an evaluation requires the simultaneous consideration of multiple, often conflicting criteria related to technical performance, resource characteristics, economic feasibility, and environmental sustainability [9,10]. Multi-Criteria Decision-Making (MCDM) methods provide a systematic framework for addressing these challenges by enabling the comprehensive assessment and ranking of alternatives based on diverse evaluation criteria [11]. Owing to their ability to support complex decision processes under uncertainty, MCDM approaches have been extensively applied in hydrogen production studies and various coal-related research fields, demonstrating their effectiveness in identifying optimal alternatives and supporting strategic energy planning [12,13]. There are some fundamental distinctions in MCDM problems. Problems where data is available can be solved using objective methods [14,15], while in situations where complete uncertainty prevails, solutions are sought using fuzzy sets based on linguistic terms [16,17]. The problem addressed in this study is not an area where there is enough clarity of information for decision-makers to make decisions with a single membership degree, as in classical fuzzy sets. This is because expert opinions differ, linguistic expressions are unclear, and sufficient data is not available in the field. The use of coal as a source for sustainable hydrogen supply is currently being debated in the literature [18]. However, sample collection, subjecting it to special heat treatments, and having suitable laboratory conditions are costly in terms of time and budget. Therefore, this study fills an important gap in the literature. Field experts evaluate the problem without having to endure all these costly processes in an environment of uncertainty and indecision.

To cope with all these challenges, a useful methodology has been proposed to the literature. First, to eliminate the uncertainty and to benefit from the opinions of different field experts, the hesitant fuzzy (HF) cluster was used in accordance with the literature [19–21]. To determine the criterion weights, the hesitant extension of the step-wise weight assessment ratio analysis (Swara) method, introduced to the literature by Keršuliene et al. (2010) [22], was used [23]. For alternative coals, the Alternative Ranking Technique based on Adaptive Standardized Intervals (ARTASI), developed by Pamucar et al. (2024) [24], was used. The integration of these two methods has been carried out for the first time in the literature. The main reasons for the development of this methodology are that it can cope with the hesitations of experts on the importance weights of the criteria, while also minimizing deviations based on normalization and being both innovative and based on their expertise in coal. This study contributes in several ways: (1) expands the literature on hydrogen (H_2) production from coal, which has large reserves worldwide, using a pyrolysis process known as a thermochemical method; (2) provides foresight to decision-makers by eliminating special permits, sampling procedures, laboratory experiments, and temporal and budgetary costs; (3) increases reliability by involving field experts in the problem; (4) provides solutions to problem areas experiencing similar problems by introducing a new methodology to the literature; (5) develops sensitivity scenarios with parametric tests to prove the accuracy

of the results. Furthermore, no studies addressing coal-derived hydrogen production using fuzzy MCDM were found.

This study presents a comprehensive methodology for evaluating different coal alternatives to ensure sustainable hydrogen production. Section 2 contains the literature review. Section 3 introduces the methods. Section 4 shares the application and findings. Section 5 contains the sensitivity analyses, Section 6 explores the discussion, and Section 7 contains the results.

2. Literature Review

Since its introduction to the literature, the SWARA method has been the subject of many studies [25–31]. In addition, it has been used as a solution tool with its fuzzy extensions in problems where determinism is replaced by uncertainty and data cannot be obtained [32–37]. These studies include those in the field of sustainable energy [38,39] as well as studies related to hydrogen processes [40,41]. On the other hand, there are also studies that aim to improve the performance of the pyrolysis process by examining the factors affecting the process with Fuzzy SWARA [42]. In their study in Turkey to determine the best hydrogen energy production method, Sagin et al. (2026) examined weights using Fermatean fuzzy SWARA to eliminate uncertainty and ranked alternatives using ARTASI [43]. The results ranked steam methane reforming as the most suitable technology for Turkey, followed by coal gasification in second place, and electrolysis and biomass gasification in third and fourth place, respectively. Instead of the Fermatean Fuzzy Set proposed in the study, a HF Set is proposed in this work. This is due to the importance of the criteria and the attempt to measure the performance of alternatives. The study, which addresses the degree of success or failure of alternative systems, is an important resource for the literature. The coal alternatives recommended in that study are considered in this work. A similar approach was also used for the Pythagorean fuzzy SWARA-ARTASI method to identify and prioritize cybersecurity risks associated with Internet of Things (IoT) applications in the retail sector [44]. Therefore, the fuzzy set is modified according to this study's needs, and a new methodology is proposed to fill a gap in the literature.

Although the extension of the HF SWARA method with ARTASI is proposed for the first time in this study, its integration with different methods exists in different studies. For example, it has been used in supplier selection [45], sustainable airport design [46], online education [47], education 4.0 [48], big data [49], and some mathematical forms [50,51].

The second method of this study, ARTASI, is one of the relatively new solution alternatives in the literature. It has been integrated with methods used in different studies with picture fuzzy [52], spherical fuzzy [53–55], Dombi-Bonferroni with ARTASI [56], and q-rung orthopair fuzzy [57] clusters.

3. Methodology

This section describes the methodology, which consists of the integration of two methods. The flow chart, including the steps of the HF-SWARA-ARTASI hybrid approach, is shared in Figure 1. Section 3.1 contains the HF-SWARA steps and formulations, while Section 3.2 contains the ARTASI method steps and formulations.

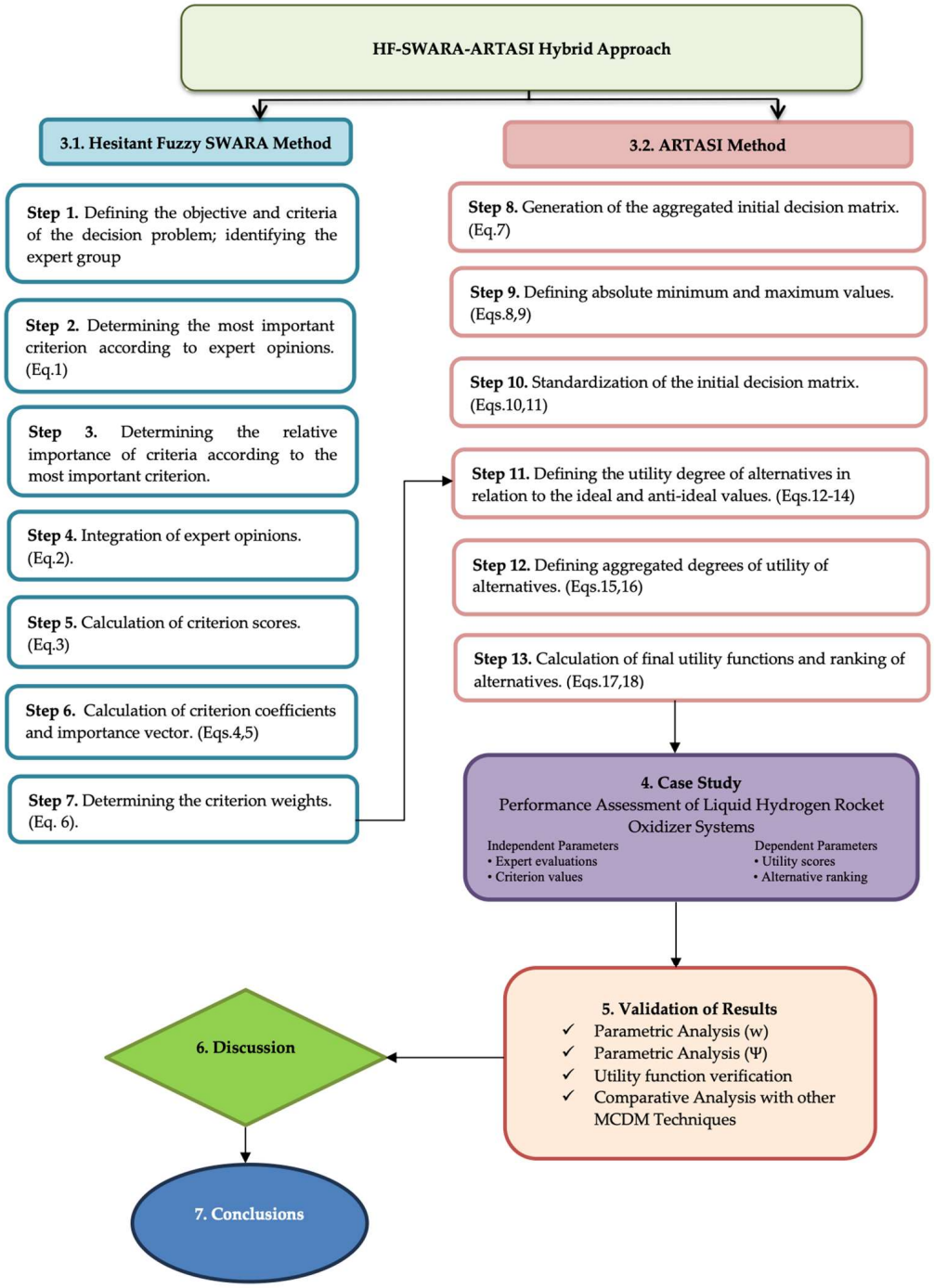

Figure 1. HF-SWARA–ARTASI hybrid approach.

Figure 1 illustrates the overall framework of the proposed HF-SWARA–ARTASI methodology. The flow chart begins with the determination of criterion weights using HF-SWARA, followed by the ranking of alternatives through the ARTASI method. The case study explicitly distinguishes the independent parameters (input criteria and expert evaluations) from the dependent parameters (utility values and alternative rankings). Finally, the validation stage includes parametric analyses based on the W and Ψ parameters together with comparative analyses using alternative MCDM methods to verify the robustness and consistency of the proposed framework.

3.1. Hesitant Fuzzy SWARA Method

This section describes the steps of the HF-SWARA method [23].

Step 1: Defining the objective and criteria of the decision problem; identifying the expert group.

The first step in applying SWARA is to define the objective of the decision problem and the criteria affecting that objective. This step also involves identifying the expert group whose opinions will be consulted in determining the decision.

Step 2: Determining the most important criterion according to expert opinions.

Each member of the expert group is asked to indicate the order of importance of the criteria affecting the decision. Let us assume that the criterion c_j $(j = 1, 2, 3, \ldots, n)$ will be evaluated by the expert group member u_k $(k = 1, 2, 3, \ldots, p)$ with a ranking of t_{jk}. If it is assumed that each expert's opinion has equal value, the overall ranking of the criterion c_j is t_j, which is the average of the ranking values determined by the expert group as given in Equation (1). In cases where expert opinions have different importance, it is also possible to combine expert opinions through weighted sums.

$$\bar{t}_j = \sum_{k=1}^{p} t_{jk} / p \tag{1}$$

Step 3: Determining the relative importance of criteria according to the most important criterion.

Each member of the expert group is asked to state the relative importance of each criterion influencing the decision, relative to the most important criterion, using unstable fuzzy linguistic terms from set S. The decision-maker can express their opinion with a single linguistic term, or with two or more linguistic terms using the conjunction "between".

S = {S_0 = very little importance, S_1 = very strongly little importance, S_2 = strongly little importance, S_3 = very little importance, S_4 = slightly little importance, S_5 = equal importance, S_6 = slightly more importance, S_7 = much more importance, S_8 = critical level importance}.

As an example of representing opinions, when a decision-maker uses the term "very little importance," their opinion is shown as {S_3}, while their opinion expressed as "between equal importance and much more importance" is shown as {S_5, S_6, S_7}.

Step 4: Integration of expert opinions.

In this step, before applying the HFLWA aggregation operator, the hesitant fuzzy linguistic term sets provided by different decision-makers must contain the same number of linguistic terms. Therefore, if the hesitant fuzzy linguistic term sets have different cardinalities, they are equalized following the preprocessing procedure adopted in the Hesitant Fuzzy SWARA literature [23,58,59]. This preprocessing is required to ensure the consistent application of the aggregation operator and does not constitute an additional assumption introduced in this study. After equalization, the hesitant fuzzy linguistic assessments are aggregated using the HFLWA operator given in Equation (2).

$$HFLWA(H_1, H_2, \ldots, H_P) = \left(\sum_{k=1} p \oplus \omega_k H_k\right) = \bigcup S_{\alpha_k} \in H_k \left\{ s_{\int_{k=1}^{p} \omega_k \alpha_k} \right\} \tag{2}$$

In the formula, $H_1, H_2, \ldots, H_P$ are the unstable fuzzy linguistic sets to be integrated, ω_k is the degree of importance given to the opinion of the k-th member of the expert group, and α_k is the linguistic terms used in the evaluation made by the k-th expert.

Unlike Analytic Hierarchy Process (AHP)-based approaches, the Hesitant Fuzzy SWARA method does not incorporate a consistency ratio for expert judgments. Instead, the individual hesitant fuzzy linguistic evaluations are aggregated using the HFLWA operator to obtain a collective assessment.

Step 5: Calculation of criterion scores.

In this step of the method, the criterion score (S_j) is calculated using the values in the integrated expert opinions, and the linguistic term sets are reduced to a single value. The criterion score is calculated using the score function given by Equation (3):

$$\rho(H_s) = \frac{1}{L}\sum_{l=1}^{L}\frac{\varphi_1}{\#H-1} \tag{3}$$

When calculating the score of the unstable fuzzy set H_s; L represents the number of elements in the set, φ_l represents the set elements, and #H represents the total number of elements in the linguistic scale.

Step 6: Calculation of criterion coefficients and importance vector.

In this step, the most important criterion is also taken into account. The criterion coefficients (K_j) are calculated by adding 1 to the criterion scores calculated for the other criteria, and the coefficient for the most important criterion is taken as 1 (Equation (4)).

$$K_j = \begin{cases} 1 & j = 1 \\ S_j + 1 & j > 1 \end{cases} \tag{4}$$

Next, the significance vector is calculated. In the significance vector, the value of the most significant vector (T_j) is assumed to be 1. As stated in Equation (5), for the other criteria, the value in the significance vector is calculated by dividing the criterion coefficient by the significance vector value of the previous criterion, which has a higher significance.

$$T_j = \begin{cases} 1 & j = 1 \\ \frac{T_{j-1}}{K_j} & j > 1 \end{cases} \tag{5}$$

Step 7: Determining the criterion weights.

In the final step of the method, the criterion weights are calculated by normalizing the importance vector. Normalization is performed by dividing the elements of the importance vector by the sum of the elements, as shown by Equation (6).

$$W_j = \frac{T_j}{\sum_{j=1}^{n} T_j} \tag{6}$$

3.2. ARTASI Method

The steps of the ARTASI method are shared in this section [24].

Step 8: The aggregated decision matrix is created using Equation (7).

$$\Delta = \begin{matrix} A_1 \\ A_2 \\ \vdots \\ A_M \end{matrix} \begin{bmatrix} \wp_{11} & \wp_{12} & \cdots & \wp_{1n} \\ \wp_{21} & \wp_{22} & \cdots & \wp_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \wp_{m1} & \wp_{m2} & \cdots & \wp_{mn} \end{bmatrix} \tag{7}$$

Step 9: The minimum and maximum values are calculated using Equations (8) and (9).

$$\wp_j^{max} = \underset{1\le i\le m}{max}\left(\wp_{ij}\right) + \left\{\underset{1\le i\le m}{max}\left(\wp_{ij}\right)\right\}^{1/m} \tag{8}$$

$$\wp_j^{max} = \underset{1\le i\le m}{min}\left(\wp_{ij}\right) - \left\{\underset{1\le i\le m}{min}\left(\wp_{ij}\right)\right\}^{1/m} \tag{9}$$

Step 10: Standardization of the matrix is achieved using Equations (10) and (11).

$$\phi_{ij} = \frac{\Psi^{(u)} - \Psi^{(l)}}{\wp_j^{max} - \wp_j^{min}} \wp_{ij} + \frac{\wp_j^{max} . \Psi^{(l)} - \wp_j^{min} . \Psi^{(u)}}{\wp_j^{max} - \wp_j^{min}} \quad (10)$$

$$\zeta_{ij} = -\phi_{ij} + \underset{1\le i\le m}{max}(\phi_{ij}) + \underset{1\le i\le m}{min}(\phi_{ij}) \quad (11)$$

Step 11: The utility degrees, as well as the ideal and anti-ideal values, of the alternatives are defined using Equations (12)–(14).

$$\vartheta_{ij}^{+} = \frac{\zeta_{ij}}{\underset{1\le i\le m}{max}(\zeta_{ij})} . w_j . \Psi^{(u)} \quad (12)$$

$$\vartheta_{ij} = \frac{\underset{1\le i\le m}{min}(\zeta_{ij})}{\zeta_{ij}} . w_j . \Psi^{(u)} \quad (13)$$

$$\vartheta_{ij}^{-} = -\vartheta_{ij} + \underset{1\le i\le m}{max}(\vartheta_{ij}) + \underset{1\le i\le m}{min}(\vartheta_{ij}) \quad (14)$$

Step 12: The aggregated degrees for the alternatives are determined using Equations (15) and (16).

$$\tilde{S}_i^{+} \sum_{j=1}^{n} \vartheta_{ij}^{+} \quad (15)$$

$$\tilde{S}_i^{-} \sum_{j=1}^{n} \vartheta_{ij}^{-} \quad (16)$$

Step 13: The final utility degrees are ranked using Equations (17) and (18).

$$\Omega_i = (\tilde{S}_i^{+} + \tilde{S}_i^{-}) \{\alpha . f(\tilde{S}_i^{+})^{\Psi} + (1-\alpha) . f(\tilde{S}_i^{-})^{\Psi}\}^{1/\Psi} ; \varphi \in [1, +\infty); \alpha \in [0, 1] \quad (17)$$

$$\Omega_i = (\tilde{S}_i^{+} + \tilde{S}_i^{-}) \{0.5 f(\tilde{S}_i^{+}) + 0.5 f(\tilde{S}_i^{-})\} \quad (18)$$

4. Case Study

Hydrogen, which is not a natural energy source, requires different sources for its production, and coal is one of them [60,61]. However, determining which coal alternative is more suitable for this is an important area of research, and experimental studies have been conducted with different coal alternatives in the literature. In this study, considering the coal reserves in the USA, five alternatives were examined with a comprehensive and novel methodology. The criteria for applying the first part of the methodology shared in Section 3 were determined based on the analyses in the study by Donaldson et al. (2025) [18] and from the literature [62–64]. The evaluation criteria were selected based on expert knowledge and previous literature to represent different aspects of system performance. Although some criteria are naturally related, each criterion reflects a distinct decision perspective and was therefore retained in the evaluation framework. The hierarchical structure is shared in Figure 2. Red colors indicate cost-related criteria, while green colors indicate benefit-related criteria.

Figure 2 presents the decision model adopted in this study. The model includes all evaluation criteria together with their corresponding decision conditions, indicating whether each criterion is of the benefit type (to be maximized) or the cost type (to be minimized). These conditions are subsequently used in the construction and evaluation of the decision matrix about coal.

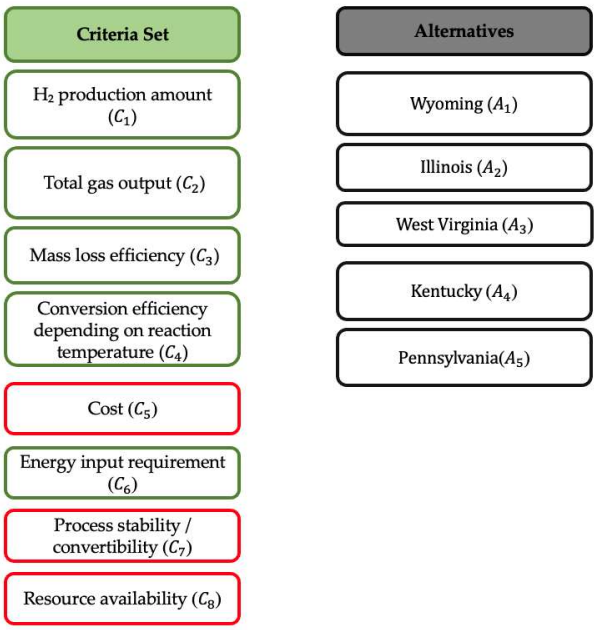

Figure 2. Decision model.

The first step in Section 3.1 is completed with the creation of the structure shown in Figure 2. The next step is to identify the most important criteria by gathering expert opinions. The experts were asked to rank the importance of the criteria. Then, the equation was combined with Equation (1) and is presented in Table 1.

Table 1. Priority ranking of criteria.

Criteria	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8
DM_1	1.00	3.00	7.00	2.00	6.00	5.00	4.00	8.00
DM_2	1.00	2.00	8.00	3.00	4.00	6.00	5.00	7.00
DM_3	2.00	1.00	7.00	3.00	5.00	6.00	4.00	8.00
Average	1.33	2.00	7.33	2.67	5.00	5.67	4.33	7.67
Rank	1	2	7	3	5	6	4	8

Table 1 shows that C_1 was identified as the most important criterion as a result of combining expert opinions. In the subsequent steps of the methodology, the other criteria will be evaluated by referencing C_1. In the third step, the expert group was asked to evaluate each criterion according to C_1 using linguistic terms, and their evaluations are shared in Table 2.

Table 2. Relative importance levels of the criteria.

Criteria	DM_1		DM_2		DM_3	
C_2	s_7		s_3		s_3	s_4
C_4	s_3	s_4	s_4	s_5	s_2	
C_7	s_2	s_3	s_2	s_3	s_4	s_5
C_5	s_1	s_2	s_1	s_2	s_7	
C_6	s_0		s_0		s_6	s_7
C_3	s_2		s_2		s_1	
C_8	s_0		s_0		s_6	s_7

As part of Step 3 in Section 3.1, each decision-maker (DM_1, DM_2, and DM_3) expresses the relative importance of each criterion with respect to the most important criterion using the HF linguistic terms defined in the linguistic term set S. The individual evaluations of the three decision-makers are summarized in Table 2. After obtaining Table 2, expert opinions were combined based on criteria using an aggregation operator. For this process, if the number of elements in the linguistic term sets differed, the highest degree element from the set with fewer elements was added. This equalized the number of elements. Using the HFLWA aggregation operator defined in Equation (2), the individual HF linguistic assessments provided by DM_1, DM_2, and DM_3 for each criterion are combined into a single aggregated HF linguistic set. Before aggregation, the number of linguistic terms in each HF linguistic set is equalized by extending the sets with fewer elements, as described above. Subsequently, the linguistic terms are arranged according to their corresponding ranks presented in Table 1, and the weighted aggregation is performed. Expert opinions were not given weight in this study. The aggregated values are reported in Table 3.

Table 3. Integrated values obtained with the aggregated operator.

Criteria	Aggregated Values	
C_2	4.333	4.667
C_4	3.000	3.667
C_7	2.667	3.667
C_5	3.333	3.667
C_6	2.000	2.333
C_3	1.667	1.667
C_8	2.000	2.333

The clusters obtained from the integration of linguistic evaluations are converted into s_j values using the score function given by Equation (3). The calculation results are presented in Table 4.

Table 4. Criterion scores.

Criteria	Scores
C_2	0.5625
C_4	0.4167
C_7	0.3958
C_5	0.4375
C_6	0.2708
C_3	0.2083
C_8	0.2708

Subsequently, C_1, the most important criterion, was also added to the calculations. The calculated scores in Table 4 were converted into criterion coefficients using Equation (4), and these coefficients were converted into a significance vector using Equation (5). The elements of the significance vector were normalized using Equation (6) and converted into weight values. The final values are shown in Table 5, and the criterion weights are shown in Figure 3.

Table 5. Final values.

Criteria	Scores	Coefficient	Significance Vector	Weights	Rank
C_1		1.0000	1.0000	0.3247	1
C_2	0.5625	1.5625	0.6400	0.2078	2
C_4	0.4167	1.4167	0.4518	0.1467	3
C_7	0.3958	1.3958	0.3237	0.1051	4
C_5	0.4375	1.4375	0.2251	0.0731	5
C_6	0.2708	1.2708	0.1772	0.0575	6
C_3	0.2083	1.2083	0.1466	0.0476	7
C_8	0.2708	1.2708	0.115	0.0375	8

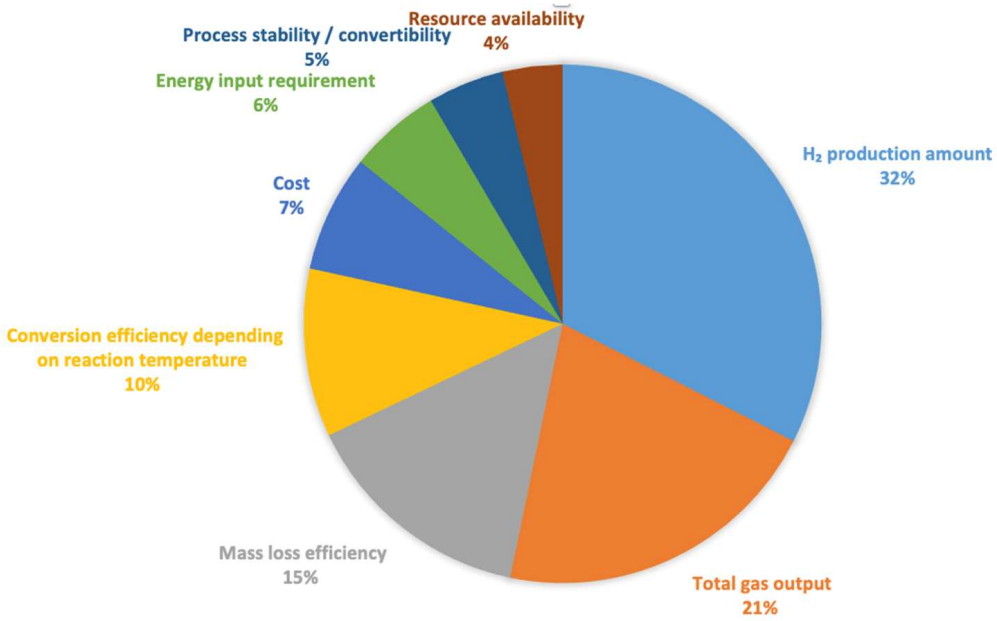

Figure 3. Weights of criteria.

When Figure 3 is examined, it can be seen that the rankings are $C_1 > C_2 > C_4 > C_7 > C_5 > C_6 > C_3 > C_8$. In this case, the most important criterion, by far, is the amount of hydrogen production. The ranking of the evaluation criteria reflects the primary objective of in situ coal pyrolysis, namely, maximizing hydrogen production while maintaining technical feasibility and process sustainability. Consequently, the hydrogen production amount (C_1) was identified as the most influential criterion, since the process's ultimate success depends directly on its ability to generate hydrogen efficiently. Total gas output (C_2) was ranked second because it represents the overall effectiveness of the pyrolysis process and is closely associated with product yield. Conversion efficiency for reaction (C_4) was monitored as a function of reaction temperature, highlighting the importance of achieving favorable production performance under varying thermal conditions. Process stability and convertibility (C_7) and cost (C_5) were also considered highly important, as reliable operation and economic viability are essential for large-scale implementation. Energy input requirement (C_6) and mass loss efficiency (C_3) were assigned relatively lower priorities since their impacts are generally reflected through the overall process performance. Finally, resource availability (C_8) was ranked as the least influential criterion because all considered coal alternatives represent major reserves within the United

States, reducing the significance of availability differences compared to production- and process-related factors.

After obtaining the criterion weights, the next step is to evaluate alternative coals for hydrogen production. The evaluations of the coals by the three experts and the initial ARTASI decision matrix obtained in step 8 based on Equation (7) are shown in Table 6.

Table 6. Initial decision matrix.

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8
A_1	8.33	8.67	7.67	8.67	6.67	7.33	8.00	9.00
A_2	7.33	7.33	6.67	7.33	7.67	6.33	6.67	8.00
A_3	6.33	6.33	5.00	6.33	5.00	4.67	7.33	6.00
A_4	5.00	5.00	5.67	5.00	6.33	5.67	5.33	7.00
A_5	3.67	4.00	3.33	4.00	4.00	3.00	5.33	5.00
$\wp_j^{max}$	9.86	10.21	9.17	10.21	9.17	8.82	9.52	10.55
$\wp_j^{min}$	2.37	2.68	2.06	2.68	2.68	1.75	3.94	3.62

For steps 9 and 10, Equations (8)–(11) were used, and the minimum and maximum values, as well as the standardization procedures, were implemented. The limits of the criterion values in Table 6 were accepted as $\Psi = 1$ and $\Psi = 100$. Then, the utility levels of the alternatives were calculated and integrated according to ideal and anti-ideal values. All these processes were calculated using Equations (12)–(16) for steps 11 and 12, respectively, as shared in Section 3.2. The standardization matrix is presented in Table 7, and the ideal and anti-ideal levels are presented in Tables 8 and 9.

Table 7. Standardization matrix.

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8
A_1	79.81	79.74	79.07	79.74	36.39	18.45	73.11	20.71
A_2	66.59	62.20	65.14	62.20	21.13	32.45	49.45	34.99
A_3	53.38	49.05	41.93	49.05	61.82	55.80	61.28	63.55
A_4	35.76	31.51	51.22	31.51	41.47	41.79	25.80	49.27
A_5	18.14	18.36	18.72	18.36	77.07	79.14	25.80	77.84
s+	79.81	79.74	79.07	79.74	77.07	79.14	73.11	77.84
s−	18.14	18.36	18.72	18.36	21.13	18.45	25.80	20.71

Table 8. Utility degrees to ideal value.

s+	**C1**	**C2**	**C3**	**C4**	**C5**	**C6**	**C7**	**C8**
A_1	32.47	20.78	14.67	10.51	3.45	1.34	4.76	1.00
A_2	27.09	16.21	12.09	8.20	2.00	2.36	3.22	1.68
A_3	21.72	12.78	7.78	6.46	5.86	4.06	3.99	3.06
A_4	14.55	8.21	9.50	4.15	3.93	3.04	1.68	2.37
A_5	7.38	4.78	3.47	2.42	7.31	5.75	1.68	3.75

Table 9. Utility degrees to anti-ideal value.

s−	C1	C2	C3	C4	C5	C6	C7	C8
A_1	32.47	20.78	14.67	10.51	5.07	1.34	4.76	1.00
A_2	31.01	19.43	13.93	9.83	2.00	3.82	3.96	2.53
A_3	28.82	17.79	11.59	9.00	6.82	5.19	4.44	3.52
A_4	23.38	13.46	12.78	6.81	5.59	4.55	1.68	3.17
A_5	7.38	4.78	3.47	2.42	7.31	5.75	1.68	3.75

To rank the coal alternatives, the general utility function was calculated using Equations (17) and (18) in step 13, the final step of the ARTASI method, which allowed for the determination of the final ranking of the alternatives presented in Table 10. As a result, rankings were obtained using the initial parameters.

Table 10. Final values and rankings.

Alt	S+	S−	S+	S−	$f(x)$	Rank
A_1	88.98	90.60	0.50	0.50	89.79	1
A_2	72.85	86.50	0.46	0.54	79.68	2
A_3	65.71	87.16	0.43	0.57	76.44	3
A_4	47.44	71.42	0.40	0.60	59.43	4
A_5	36.54	36.54	0.50	0.50	36.54	5

Initial results based on HF-SWARA and ARTASI ranked the alternatives as Wyoming (A_1) > Illinois (A_2) > West Virginia (A_3) > Kentucky (A_4) > Pennsylvania (A_5). This ranking indicates that Wyoming coal exhibits the most favorable overall performance when all evaluation criteria and their respective importance weights are considered simultaneously. The superior position of Wyoming coal can be primarily attributed to its strong performance in the most influential criteria, particularly hydrogen production amount (C_1), total gas output (C_2), and conversion efficiency depending on reaction temperature (C_4). Since these criteria received the highest weights in the HF-SWARA, alternatives performing well in these aspects achieved a significant advantage in the final ranking. In contrast, Pennsylvania coal (A_5) ranked last, suggesting comparatively lower overall suitability for hydrogen production through in situ pyrolysis. The ranking further demonstrates that technical performance-related criteria exert a stronger influence on the final decision than economic and resource-based factors, emphasizing the critical role of production efficiency in the evaluation of coal resources for sustainable hydrogen generation.

5. Validation of Results

To validate the robustness of the proposed framework, a comprehensive parametric analysis was conducted by varying both the W and Ψ parameters. The resulting changes in the utility values and alternative rankings were examined to evaluate the stability of the proposed approach. In addition, the obtained rankings were compared with those produced by other MCDM techniques to further verify the consistency and reliability of the proposed methodology.

To comprehensively validate the proposed HF-SWARA–ARTASI framework, three complementary validation analyses were conducted. Figures 4–6 present the results of the parametric analyses and comparative evaluation, which collectively assess the robustness, stability, and consistency of the proposed methodology under different parameter settings.

The first parametric test was applied to the variation of w values between 0.1 and 1 in the ARTASI method. The order of the alternatives remained unchanged for the w parameter. The results can be examined through Figure 4.

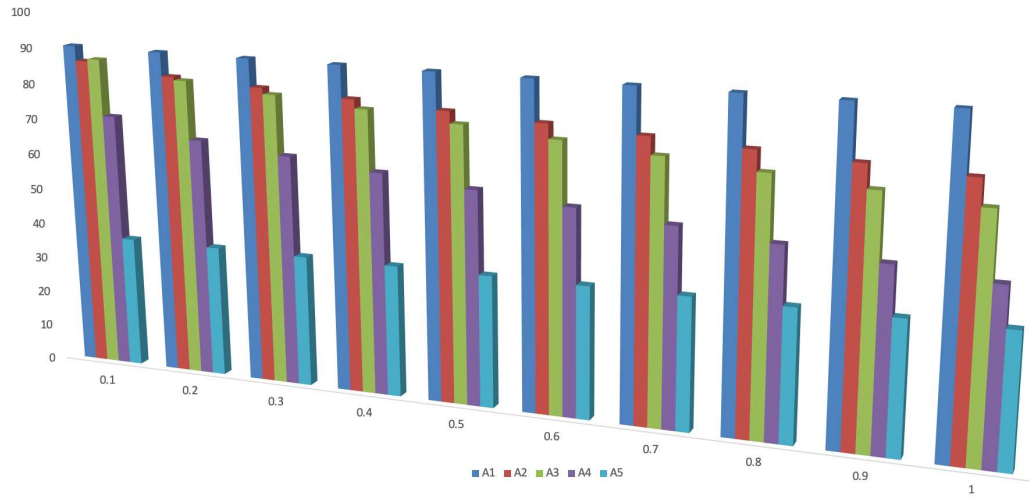

Figure 4. Rankings of alternatives based on parameter w.

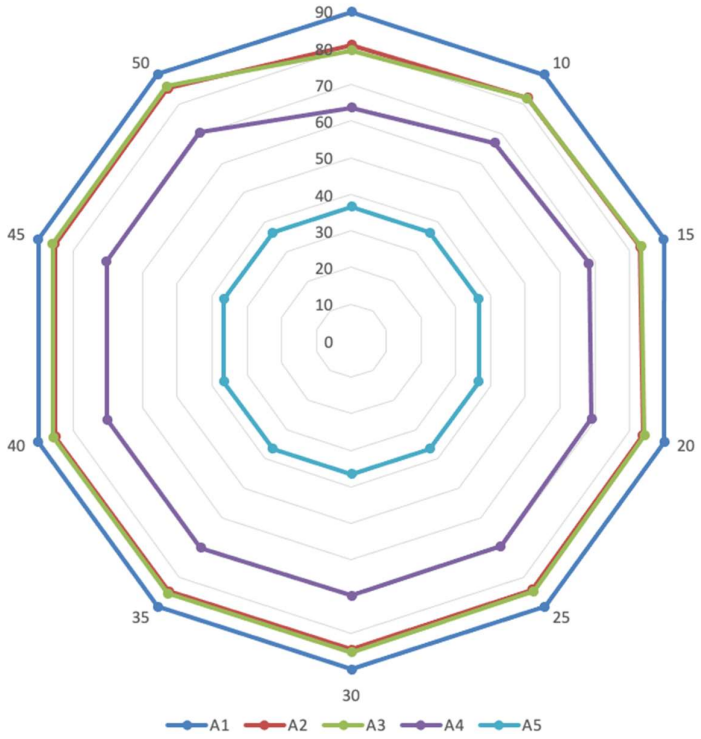

Figure 5. Rankings of alternatives based on parameter Ψ.

The results presented in Figure 4 demonstrate that the ranking remains stable under different values of parameter W, confirming the robustness of the proposed method.

The second parametric test was performed for Ψ values. The results were examined by varying Ψ values between 5 and 50. Figure 5 shows the scores of the coal alternatives.

Figure 5 shows that variations in the Ψ parameter have only a limited influence on the final ranking, indicating the stability of the decision-making framework. When Figure 5 is examined, it is observed that the general rankings are $A_1 > A_2 > A_3 > A_4 > A_5$, with alternatives 2 and 3 occasionally swapping places with slight differences. This means that if the first coal source is not feasible, these alternatives can be used interchangeably.

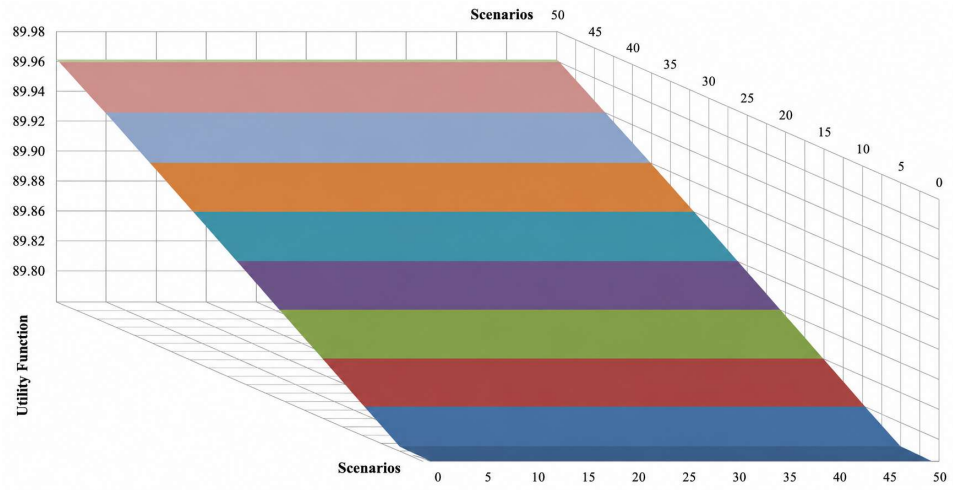

Figure 6. Variation of parameters φ and changes in utility functions of the best alternative.

Additionally, another analysis was conducted to analyze the utility function values of the best alternative. Figure 6 allows for this analysis.

Figure 6 presents a robustness validation of the proposed model by perturbing the utility function values of the best-ranked alternative. The purpose is to evaluate the stability of the ranking results under slight variations in utility values, rather than comparing different MCDM methods. The observed consistency confirms that the proposed framework yields stable and reliable results. When Figure 6 is examined, it can be seen that the values for alternative A_1 are increasing steadily. Therefore, it can be seen that the results of the proposed methodology maintain their robustness.

Finally, the results were compared with current and older but robust MCDM methods. For comparative calculations, Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS), Multi-Attributive Border Approximation Area Comparison (MABAC), Ranking of Alternatives through Functional Mapping of Criterion Sub-intervals into a Single Interval (RAFSI), COmbinative Distance-based ASsessment (CODAS), Evaluation based on Distance from Average Solution (EDAS) and Additive Ratio ASsessment (ARAS) methods were used. Figure 7 examined the results show the superiority of the first two alternatives, with minor differences in the third and fourth positions, and the last coal alternative consistently ranking last in all calculations.

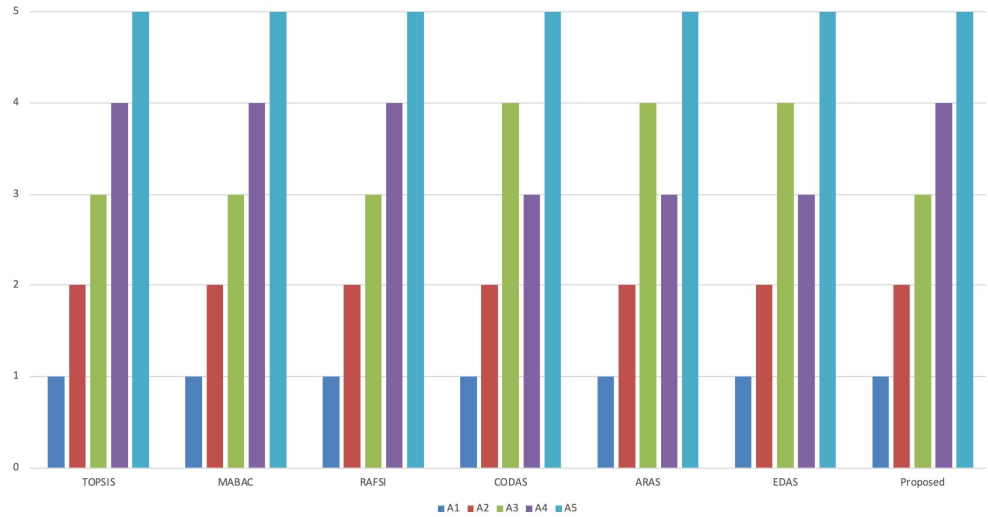

Figure 7. Comparative analyses.

Overall, the validation framework is designed to assess the robustness, stability, and consistency of the proposed decision-making model rather than predictive accuracy. The sensitivity analysis based on utility function perturbation demonstrates the stability of the best-ranked alternative under small variations. The parameter analysis further confirms the resilience of the model with respect to key parameter changes. Finally, the comparative analysis with existing MCDM methods validates the consistency of the ranking outcomes. These complementary evaluations collectively confirm the reliability and robustness of the proposed approach.

6. Discussion

This section includes a discussion of the physicochemical properties of the coals examined, in addition to the MCDM analyses. Table 11 contains summary information.

Table 11. Typical physicochemical properties of the investigated coal types.

Alt	Coal Rank	Moisture (%)	Volatile Matter (%)	Fixed Carbon (%)	Ash (%)	Carbon (%)	Hydrogen (%)	Reactivity in Pyrolysis
A_1	Sub-bituminous	20–30	35–45	35–45	4–8	65–72	4.5–5.5	Very High
A_2	High-volatile Bituminous	8–15	30–40	45–55	8–15	70–78	4.5–5.5	High
A_3	Bituminous	2–8	20–35	50–65	5–12	75–85	4.0–5.0	Moderate
A_4	Bituminous	3–10	20–35	50–65	5–15	75–85	4.0–5.0	Moderate
A_5	Anthracite	2–6	2–10	75–90	5–15	85–92	2.5–4.0	Low

Examining Table 11, the obtained ranking can be physically justified by the intrinsic characteristics of the investigated coal types. Wyoming coal, which is generally classified as sub-bituminous coal, contains substantially higher volatile matter and exhibits greater pyrolytic reactivity than the other alternatives. These characteristics facilitate devolatilization and the formation of hydrogen-rich gaseous products during thermal decomposition. Conversely, Pennsylvania coal, predominantly anthracitic in nature, possesses low volatile matter content and a highly carbonized structure, resulting in reduced reactivity and lower hydrogen production potential. Illinois coal demonstrates intermediate behavior, combining relatively high volatile matter content with favorable economic characteristics. Therefore, the ranking generated by the proposed MCDM framework is supported not only by expert judgments but also by the fundamental physicochemical properties governing coal pyrolysis.

7. Conclusions

This study focuses on the evaluation and prioritization of coal alternatives for hydrogen production through in situ pyrolysis, considering five coal resources with large reserves in the United States. In this context, a novel and robust decision-making framework was proposed. First, the critical criteria affecting hydrogen production were identified based on an extensive literature review. Determining the relative importance of these criteria is a challenging task due to the uncertainty and hesitation inherent in expert judgments. Therefore, the HF-SWARA method was employed to address decision-makers' hesitations and obtain more reliable criterion weights. Subsequently, the coal alternatives were evaluated by experts experienced in in situ pyrolysis using the ARTASI method. The results indicate that the coal alternatives can be ranked as Wyoming > Illinois > West Virginia > Kentucky > Pennsylvania in terms of their overall suitability for hydrogen production through in situ pyrolysis.

The results of the study are evaluated from both quantitative and qualitative perspectives to ensure a comprehensive assessment of the proposed decision-making framework. From a quantitative perspective, an extensive scenario analysis is conducted to examine the robustness of the model under varying conditions. Specifically, three different scenario groups are considered: (i) ten scenarios with weight variations in the range of 0.1 to 1, (ii) ten scenarios with extended parameter variations in the range of 5 to 50, and (iii) eleven scenarios based on utility function perturbations within the range of 0 to 50. These scenarios collectively demonstrate the stability of the proposed approach under a wide spectrum of decision environments.

In addition, the proposed method is benchmarked against three widely used MCDM techniques to further validate its reliability. The comparative results indicate a high degree of consistency between the proposed approach and existing methods, with only minor variations in ranking outcomes. This consistency confirms the robustness and methodological soundness of the proposed framework.

From a qualitative perspective, the results demonstrate that the integration of the weighting mechanism and ranking procedure provides a stable and interpretable decision-making structure. The negligible deviations observed across different scenarios and comparative methods further strengthen the credibility of the proposed model in handling uncertainty and parameter variability.

Overall, both scenario-based analysis and comparative evaluation confirm that the proposed method produces stable, consistent, and reliable results across different decision environments.

In summary, this research contributes to the sustainable energy literature by proposing the integrated HF-SWARA–ARTASI framework for the evaluation of coal alternatives for hydrogen production through in situ pyrolysis. Beyond its application to coal resource assessment, the proposed approach contributes to ongoing discussions on energy transition, energy security, and sustainable resource utilization. By integrating sustainability considerations, energy technologies, and decision-making methodologies, the framework provides a systematic tool for addressing complex energy planning problems.

Despite this expertise, the problem was solved in a fuzzy environment for academic rigor. Expert opinions are crucial in such critical problems, and finding experts is very difficult. The study was conducted on a sample group of reserves in the United States. Testing the proposed model with reserves in different countries would be valuable for future studies. However, it should be noted that verifying the results requires laborious processes related to the reserves, special permits, and laboratory environments. From another perspective, in future research, HF sets can be extended with different operators or combined with other fuzzy set theories to increase the accuracy of the results. While several evaluation criteria may exhibit conceptual relationships, the proposed framework relies on expert opinion to assess their relative importance. Future studies using objective data-based methods could compare the accuracy of experimental results with MCDM. Because this study is fuzzy set-based, statistical multicollinearity analysis, which could be considered in future studies using data-driven weighting approaches, was not performed. On the other hand, studies that produce solutions with ARTASI integrations using methods other than SWARA can be expanded.

Author Contributions: Conceptualization, A.A. and H.A.D.; methodology, H.A.D.; software, N.Y., A.A., H.A.D. and N.Y.; validation, A.A., B.D., H.A.D. and N.Y.; formal analysis, A.A., B.D., H.A.D. and N.Y.; investigation, B.D. and N.Y.; resources, A.A., H.A.D. and N.Y.; data curation, A.A., B.D., and N.Y.; writing—original draft preparation, A.A., B.D., H.A.D. and N.Y.; writing—review and editing, A.A., B.D., H.A.D. and N.Y.; visualization, H.A.D.; supervision, B.D. and N.Y.; project administration, B.D. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Data Availability Statement: The raw data supporting the conclusions of this article will be made available by the authors on request.

Conflicts of Interest: The author declares no conflicts of interest.

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