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Multi-Criteria Decision Framework for Performance Evaluation of Liquid Hydrogen Rocket Fuel Systems with Different Oxidizers

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Abstract

The use of liquid hydrogen (LH_2) in rocket propulsion systems is among the most critical technologies enabling highly efficient space exploration. Fuel-oxidizer combinations directly impact mission performance, safety, and sustainability. In the literature, determining which oxidizer to use to obtain an efficient combination in experimental studies is a valuable area of research. However, evaluating different alternatives according to various criteria in experimental studies is expensive, time-consuming, and quite dangerous. This study aims to provide decision-makers with analytical support through a novel multi-criteria decision-making methodology. In this context, the simple weight calculation (SIWEC) method is integrated to determine the weights of the criteria, and the mulTi-noRmalization mUlti-distance aSsessmenT (TRUST) method is integrated to evaluate the oxidizers. The results show that the most important criterion is combustion, followed by environmental sustainability, applicability, cost, and operational safety. The foremost oxidizer, according to the analyses, parametric sensitivity analysis scenarios, and comparative analyses, is overwhelmingly LH_2-liquid oxygen (LOX). In all analyses, fluorine (F_2) ranked second, followed by the FLOX mixture in third place, and ozone (O_3) in last place. In addition, sensitivity analyses based on α and β parameter variations and comparative analyses were conducted to evaluate the robustness and stability of the proposed decision-making framework.

Keywords: rocket propulsion; liquid hydrogen; alternative oxidizer; multi-criteria decision making; performance evaluation

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1. Introduction

Rocket propulsion systems constitute one of the most critical technological components of modern space exploration, enabling satellite deployment, deep space missions, military operations, and human spaceflight [1,2]. Rocket fuels are generally classified as solid, liquid, and hybrid systems, while liquid fuels can be further categorized as cryogenic, hypergolic, and non-hypergolic (anargolic) combinations based on their ignition and storage characteristics [3,4].

Among these systems, cryogenic fuels, particularly LH_2, continue to attract significant interest due to their high specific thrust, clean combustion characteristics, and suitability

for high-efficiency propulsion applications [5,6]. In contrast, hypergolic fuels offer reliable spontaneous ignition capability and long-term storability, but are generally associated with toxicity, corrosiveness, and environmental concerns. With the increasing demand for sustainable and high-performance propulsion technologies in next-generation space missions, the optimization of LH_2-based fuel-oxidizer combinations has become increasingly important [7]. Due to its superior combustion performance and sustainability, hydrogen is expected to continue playing a significant role as a fuel in future propulsion systems [8].

The performance of LH_2 propulsion systems depends not only on the fuel itself but also on the oxidizer used to convert chemical energy into thrust [9]. Different oxidizers can substantially influence combustion efficiency, operational safety, storage requirements, environmental sustainability, feasibility, and overall system cost. For this reason, the effects of oxidizer selection on LH_2 propulsion performance are investigated using specialized simulation and analysis tools developed by organizations such as the National Aeronautics and Space Administration NASA [10]. However, access to these software platforms often requires special authorization, considerable technical expertise, and high computational and financial resources. At this point, examining different oxidizer alternatives under multiple factors highlights a significant decision problem. This problem structure is expressed in the literature as Multi-Criteria Decision Making (MCDM) and is useful in solving various problems [11–13]. It has also served as a solution tool for a limited number of studies related to rockets [14,15].

MCDM problems fundamentally consist of two main elements in terms of main calculations: the weighting of criteria and the ranking of alternatives. The choice of which method to use is critical at this stage. The structure of the problem needs to be thoroughly evaluated. Furthermore, a methodology should be established that not only serves as an application but also makes an original contribution to the literature. Therefore, a novel and hybrid MCDM framework is presented in this study. For weighting the criteria, the simple weight calculation (SIWEC) method, introduced to the literature by Puška et al. [16] and one of the most current solution techniques, was used. For ranking alternatives, the mulTi-noRmalization mUlti-distance aSsessmenT (TRUST) method, introduced to the literature by Torkayesh and Deveci [17], was preferred. The integration of these two methods is achieved for the first time in the literature. There are key arguments behind this hybrid integration. The first is to leverage the power of the SIWEC method, which allows decision-makers to evaluate criteria without the need for fuzzy and computationally complex approaches. Since rocket and LH_2-based processes are demanding, expensive, and time-consuming, this approach allows the impact of criteria to be incorporated into the problem in a simple yet effective way. The second is to utilize the TRUST method, avoiding the conventional singular procedures of the literature, and to conduct an effective alternative evaluation through multiple normalization steps from four different perspectives and a two-step distance-based assessment.

Propulsion systems used in spacecraft have been a significant research topic in recent years [18–20]. Liquid-fueled rockets are one of the vehicles studied in this field. Since experimental studies on these vehicles are both time-consuming and costly, theoretical analyses are recommended first [21–23]. The main challenge regarding LH_2 used in rockets lies in the oxidizers. The necessity of researching oxidizer options that will provide an advantage in thrust has been emphasized in the literature [9]. Investigating alternative oxidizers under multiple criteria to achieve the highest performance is a problem that can be examined without relying on experiments using MCDM. Since addressing this problem requires specialized expertise and remains underexplored in the literature, this study provides a novel contribution by addressing an important research gap.

This study offers several important contributions: (i) addressing the problem of oxidizers necessary for the effective use of LH_2, indispensable for space missions; (ii) avoiding the dangers and experimental processes of a laboratory environment; (iii) saving time and budget by consulting with field experts; (iv) developing a robust MCDM framework that can be used for other decision problems in the literature; and (v) performing sensitivity scenarios through parametric tests and comparative analyses with different methods to verify the validity of the results. However, no similar study has been found in the literature regarding oxidizers. The literature lacks a multidimensional evaluation of LH_2 oxidizers used in rockets. Although individual oxidizers are known in propulsion studies, the discussion of their performance with LH_2 using systematic approaches is quite limited in the literature. This study aims to fill an important gap by considering combustion performance and safety perceptions together with costs. In this context, the present study proposes a comprehensive framework for the evaluation of oxidizers based on MCDM principles.

In this context, the study is divided into detailed sections, and the processes within the comprehensive framework are examined analytically at each step. Section 2 presents a literature review of the methods used. Section 3 introduces the methodological framework of the proposed SIWEC-TRUST hybrid method, providing a detailed explanation of its procedural steps and theoretical foundations. Section 4 conducts a case study for LH_2 oxidizers used in rocket propulsion systems. Section 5 performs the validation procedures for the calculations made for the case study by conducting different scenario and comparison analyses. Finally, Section 6 evaluates the obtained results.

2. Literature Review

This section presents a literature review of the methods to be used to find an answer to this research problem.

The first stage in MCDM methodologies is reflecting the importance levels of the criteria in the problem. The literature on the SIWEC method for criterion weights has been examined. Cao et al. attempted to select a strategy in their studies on how to optimize digital twin technologies for sustainable smart cities [24]. While the criterion weights were evaluated using the SIWEC method, the strategies were ranked using the simple additive weighting (SAW) method. Kaya used the integration of Geographic Information Systems (GIS) with Fuzzy Logarithm Methodology of Additive Weights (FLMAW)-Fuzzy SIWEC for the design and optimization of green and safe micro-mobility routes [25]. Badi et al. determined the criterion weights for railway infrastructure planning using the SIWEC method, while evaluating strategic railway development alternatives using the Ranking Alternatives by Weighted Criteria Evaluation (RAWEC) method [26]. Aytekin and Korucuk focused on the uncertainty environment to evaluate the elements of sustainability performance in port operations. Therefore, the SIWEC method was proposed to the literature as Interval-valued p, q, r-Spherical Fuzzy SIWEC [27]. Sahoo and Debnath conducted a study on the site selection of hydroelectric power plants for rural development. While SIWEC was used for the importance weights of the criteria, optimal locations were examined with the Ranking Alternatives by Perimeter Similarity (RAPS) approach [28]. Çalık et al. developed an approach that also considers customer preferences for research based on e-commerce. The classical SIWEC approach was integrated with gray numbers and then integrated into the multi-objective optimization problem with the Weighted Sum Scalarization Method (WSSM) [29]. Consequently, the SIWEC method and its various versions are used as a solution tool for determining the weights of criteria in many new and diverse fields of study, depending on the needs [30–34].

The second stage in MCDM methodologies is the ranking of alternatives. Literature on the TRUST method was reviewed for ranking processes. Lu et al. determined

criterion weights using the SECA method for the location selection problem of electric vehicle charging stations and evaluated alternative locations using the TRUST method [35]. Gholian-Jouybari et al. established a soybean-based model for a closed-loop food supply network. A mixed integer linear programming model was established in a multi-objective structure, and a series of analyses were performed to validate the results. Some of these analyses were carried out using MCDM methods. The validity of the model was tested through validations performed with TRUST integration using Criteria Importance Through Intercriteria Correlation (CRITIC) [36]. Bonab et al. integrated the TRUST method with the spherical fuzzy cluster-based Best-Worst Method (BWM) for sustainable and resilient supply chain applications based on the Internet of Things [37]. Puška et al. ranked suppliers for a supplier selection study in agricultural enterprises using the Compromise Ranking of Alternatives from Distance to Ideal Solution (CRADIS) and the TRUST method [38]. Fetanat and Tayebi prioritized the sustainability and availability of solar thermal energy technologies to increase oil production. While the main method in the study was the T-spherical fuzzy set-based ordinal priority approach (T-SFS-OPA), TRUST was used in the comparative analyses [39]. Gholian-Jouybari et al. proposed a mixed integer linear programming model for an agro-food supply chain network design for the coconut industry under sustainable conditions. The CRITIC-TRUST approach was used to validate the results [40]. Yaseliani et al. preferred the TRUST method for alternatives in a decision support system based on a diagnostic algorithm to suggest the best treatment options for diseases [41]. In conclusion, the TRUST method is reliably preferred for solving problems in various fields [42,43]. In the literature, this method, which integrates methods that determine different criterion weights, is used for the first time in a hybrid form with the SIWEC method. This integration allows for the creation of a methodology that is computationally light but analytically very powerful. Thanks to this, important decision problems can be solved relatively easily, even in uncertain environments, without involving more complex and specialized calculations based on fuzzy logic.

3. Methodology

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

3.1. SIWEC Method

The SIWEC method is one of the most up-to-date methods that takes expert opinions into account in calculating criterion weights.

Step 1: Based on expert evaluation by decision-makers (dm_k), the initial decision-making problem is formulated by evaluating alternatives (a_i) according to each criterion (c_j).

Step 2: Decision-makers evaluate the criteria using linguistic terms and various scales defined by the research itself. In this study, criteria will be evaluated with defined values ranging from 1 to 10. The evaluation of criteria will be conducted within the range of absolutely bad (1) and perfect (10). Here, linguistic expressions are used first because experts need to compare the criteria. Then, the corresponding scores for the linguistic expressions are written. 1 means absolutely bad (AB), 2 very bad (VB), 3 bad (B), 4 medium-bad (MB), 5 equal (E), 6 medium good (MG), 7 good (G), 8 extremely good (EG), 9 absolutely good (AG), 10 perfect (P).

Step 3: The initial decision matrix (M) is obtained by converting the linguistic terms into numbers. This matrix is created based on the decision-maker evaluations.

$$M = \left[x_{ij}\right]_{mxn} = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1j} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2j} & \cdots & x_{2n} \\ \cdots & \cdots & \cdots & \cdots & \cdots & \cdots \\ x_{i1} & x_{i2} & \cdots & x_{ij} & \cdots & x_{in} \\ \cdots & \cdots & \cdots & \cdots & \cdots & \cdots \\ x_{m1} & x_{m2} & \cdots & x_{mj} & \cdots & x_{mn} \end{bmatrix} \quad (1)$$

Step 4: The decision matrix is normalized using Equation (2). x_{ijmax} represents the maximum value in the decision matrix.

$$n_{ij} = \frac{x_{ij}}{x_{ijmax}} \quad (2)$$

Step 5: In this step, the standard deviations of the values in the normalized matrix are calculated. By going through this process, the decision-maker, who is more realistic, will receive a higher score because the decision-maker is evaluating over a wider range of intervals.

Step 6: The normalized values are multiplied by the standard deviations $\sqrt{\frac{\sum_{i=1}^{n}(x_i - x_{avr})^2}{n-1}}$ as in Equation (3).

$$v_{ij} = n_{ij} \times st.dev_j \quad (3)$$

Step 7: The values obtained at the previous step are then summed and substituted into Equation (4).

$$s_{ij} = \sum_{j=1}^{n} v_j \quad (4)$$

Step 8: In this step, each s_{ij} value is divided by the total s_{ij} value such that the sum of the weights of the criteria is one, as in Equation (5).

$$w_{ij} = \frac{s_{ij}}{\sum_{j=1}^{n} s_{ij}} \quad (5)$$

The SIWEC method is designed to determine the relative importance of evaluation criteria in an objective manner by exploiting the information contained in the decision matrix. Rather than relying on subjective judgments from decision-makers, SIWEC evaluates the contribution of each criterion according to the distribution and discriminatory power of the performance values across the alternatives. Accordingly, each computational step serves a specific purpose: the decision matrix is first organized to represent the performance of all alternatives, followed by normalization to eliminate the influence of different measurement scales and enable meaningful comparisons among criteria. The subsequent calculations quantify the information provided by each criterion, allowing criteria with greater discriminatory capability to receive higher importance. The final step produces an objective weight vector that reflects the intrinsic informational content of the data and serves as the basis for the ranking procedure.

3.2. TRUST Method

The TRUST method is an approach that eliminates the disadvantages of using single normalization. It is a unique approach that combines different normalization techniques and different distance measures when evaluating alternatives. Furthermore, it incorporates the opinions of decision-makers into the problem by limiting them to upper and lower bounds when applying this approach.

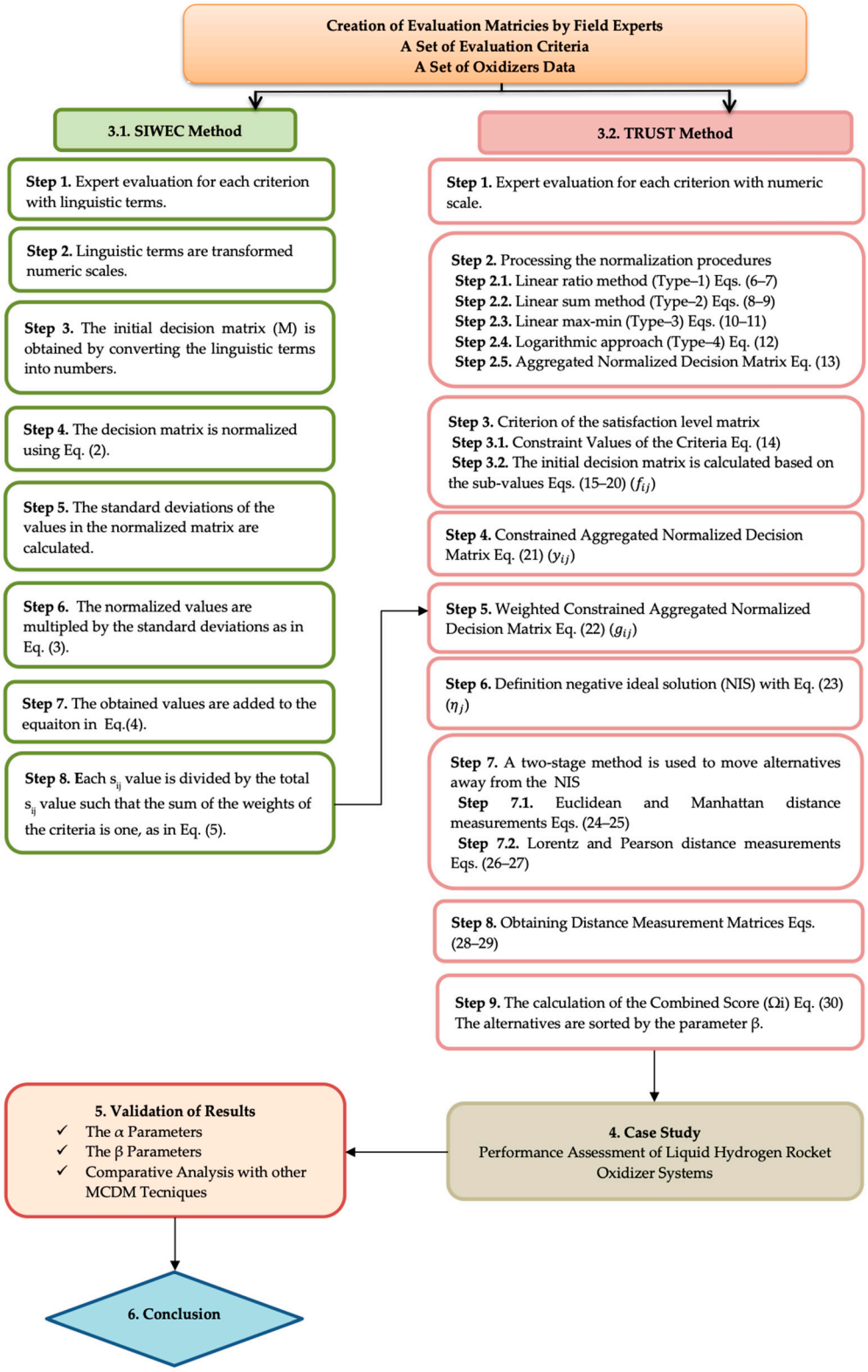

Figure 1. SIWEC-TRUST hybrid approach.

Step 1: Just like in the SIWEC method, the first step of the method begins with creating a decision matrix. Each alternative is scored using a 1–9 scale by experts based on criteria (1 shows the lowest score and 9 denotes the highest score).

Step 2. Processing the normalization procedures: The steps of the TRUST method involve a process that converts the initially generated decision matrix into a normalized decision matrix. This process is carried out using four separate normalization techniques.

Step 2.1. Normalized values are obtained from the initial decision matrix using Equations (6) and (7) with the linear ratio method (Type-1) [44].

$$x_{ij}^{a} = \frac{x_{ij}}{\max\limits_{i} x_{ij}} \tag{6}$$

$$x_{ij}^{a} = \frac{\min\limits_{i} x_{ij}}{x_{ij}} \tag{7}$$

Step 2.2. The elements of the initial decision matrix are then normalized using Equations (8) and (9) with the linear sum method (Type-2) [45].

$$x_{ij}^{b} = \frac{x_{ij}}{\sum_{i=1}^{m} x_{ij}} \tag{8}$$

$$x_{ij}^{b} = \frac{\frac{1}{x_{ij}}}{\sum_{i=1}^{m} \frac{1}{x_{ij}}} \tag{9}$$

Step 2.3. The elements in the initial decision matrix are then normalized using Equations (10) and (11) with linear max-min (Type-3) [46].

$$x_{ij}^{c} = \frac{(x_{ij} - \min\limits_{i} x_{ij})}{(\max\limits_{i} x_{ij} - \min\limits_{i} x_{ij})} \tag{10}$$

$$x_{ij}^{c} = \frac{(\max\limits_{i} x_{ij} - x_{ij})}{(\max\limits_{i} x_{ij} - \min\limits_{i} x_{ij})} \tag{11}$$

Step 2.4. The last type of normalization is a technique that facilitates the normalization of the elements of the decision matrix through a logarithmic approach (Type-4) [47]. It is performed with Equation (12).

$$x_{ij}^{d} = \frac{log(x_{ij})}{log(\prod_{i=1}^{m} x_{ij})} \tag{12}$$

Step 2.5. Combining all normalized decision matrices is performed using four parameters called α_i, thus creating the total normalized decision matrix.

$$h_{ij} = \alpha_1 x_{ij}^{a} + \alpha_2 x_{ij}^{b} + \alpha_3 x_{ij}^{c} + \alpha_4 x_{ij}^{d} \tag{13}$$

Step 3. Creating the satisfaction level matrix: Preliminary data are used to formulate the initial decision matrix for the constrained attributes. This matrix is called the satisfaction level matrix [48]. This matrix is derived based on the constraint values specified for the criteria, and each element is denoted by f_{ij}. Based on expert opinions or actual data, the values in the x_{ij}^{min} and x_{ij}^{max} matrices represent the minimum and maximum values for the respective criterion.

Step 3.1. Constraints should be established by decision-makers, taking into account their expertise and the technical competence of the criteria. Constraint values are displayed within a range limited by lower and upper constraints. The names of these elements are [LBj] and [UBj], respectively. The assigned constraint values must be between x_{ij}^{min} and x_{ij}^{max} as shown in Equation (14).

$$Co_j = [LB_j, UB_j] \subseteq \left[x_j^{min}, x_j^{max}\right] \tag{14}$$

Step 3.2. The initial decision matrix is calculated based on the sub-values. The matrix is initially represented as F. The element f_{ij} shows the satisfaction level of alternative i compared to alternative j. Equations (15)–(17) can be used to determine the F matrix elements, and Equations (18)–(20) can be used for the cost criterion.

$$f_{ij} = 1,\ if\ x_{ij} \in [LB_j, UB_j] \tag{15}$$

$$f_{ij} = 1 - \frac{LB_j - x_{ij}}{Max\left(LB_j - x_j^{min}, x_j^{max} - UB_j\right) + 1},\ if\ x_{ij} \in [x_j^{min}, LB_j] \tag{16}$$

$$f_{ij} = 1 - \frac{1 - UB_j + x_{ij}}{Max\left(LB_j - x_j^{min}, x_j^{max} - UB_j\right) + 1},\ if\ x_{ij} \in [UB_j, x_j^{max}] \tag{17}$$

$$f_{ij} = \frac{1}{Max\left(LB_j - x_j^{min}, x_j^{max} - UB_j\right) + 1},\ if\ x_{ij} \in [LB_j, UB_j] \tag{18}$$

$$f_{ij} = \frac{LB_j - x_{ij}}{Max\left(LB_j - x_j^{min}, x_j^{max} - UB_j\right)},\ if\ x_{ij} \in [x_j^{min}, LB_j] \tag{19}$$

$$f_{ij} = \frac{x_{ij} - UB_j}{Max\left(LB_j - x_j^{min}, x_j^{max} - UB_j\right)},\ if\ x_{ij} \in [UB_j, x_j^{max}] \tag{20}$$

Step 4. The aggregate normalized decision matrix calculated in Step 2 is combined with the matrix showing the extent to which the constraints are met to create a constrained aggregate normalized decision matrix. This is represented by Equation (21).

$$y_{ij} = f_{ij}\, h_{ij} \tag{21}$$

Step 5. In the fifth step of the methodology, the weight vectors of the criteria are multiplied by the constrained aggregate normalized decision matrix. The weight vector w_j shown in Equation (22) represents the weights calculated in the SIWEC method.

$$g_{ij} = y_{ij}\, w_j \tag{22}$$

Step 6. For G, defined as a weighted matrix, the negative ideal solution is calculated using Equation (23).

$$\eta_j = min\ g_{ij} \tag{23}$$

Step 7. A two-stage method is used to move alternatives away from the negative ideal solution.

Step 7.1. Euclidean and Manhattan distance measurements are used in the first stage of the two-stage method. The formulas are shared in Equations (24) and (25).

$$E_i = \sqrt{\sum_{i=1}^{m} (g_{ij} - \eta_j)^2} \tag{24}$$

$$T_i = \sum_{i=1}^{m} |g_{ij} - \eta_j| \tag{25}$$

Step 7.2. To calculate the distances of the alternatives to the negative ideal solution, Lorentz and Pearson distance measurements are applied as part of step 2. The formulas are shared in Equations (26) and (27).

$$L_i = \sum_{i=1}^{m} log(1 + |g_{ij} - \eta_j|) \tag{26}$$

$$P_i = \sum_{i=1}^{m} \frac{(g_{ij} - \eta_j)^2}{\eta_j} \tag{27}$$

Step 8. Obtaining Distance Measurement Matrices. It is clear that two relative distance evaluation matrices are defined as ET = $[\theta_{ij}]$ and LP = $[\varphi_{ij}]$.

$$\theta_{ik} = (E_i - E_k) + ((E_i - E_k) \times (T_i - T_k)) \tag{28}$$

$$\varphi_{ik} = (L_i - L_k) + ((L_i - L_k) \times (P_i - P_k)) \tag{29}$$

Step 9. The calculation of the Combined Score (Ωi) is given in Equation (30) below.

$$\Omega_i = \beta \sum_{k=1}^{n} \theta_{ik} + (1 - \beta) \sum_{k=1}^{n} \varphi_{ik} \tag{30}$$

The parameter β takes a value between 0 and 1. The alternatives are sorted from largest to smallest.

Within the TRUST procedure, each computational step serves a distinct purpose. Initially, the decision matrix is normalized using multiple normalization techniques to preserve the characteristics of the original data while reducing the impact of scale differences among criteria. Subsequently, weighted normalized values are obtained to incorporate the relative importance of each evaluation criterion into the analysis. Different distance measures are then calculated to evaluate the proximity of each alternative to the ideal solution from complementary perspectives, thereby reducing the sensitivity associated with any single distance metric. Finally, these distance-based assessments are aggregated into a unified performance index, enabling the alternatives to be ranked according to their overall performance. This integrated framework enhances the stability, reliability, and discriminatory capability of the final decision results.

4. Case Study

This section presents the application of the proposed SIWEC–TRUST framework to the oxidizer selection problem. The results are organized sequentially to reflect the stages of the proposed methodology. The decision matrix first summarizes the expert evaluations of the candidate oxidizers with respect to the predefined criteria. Based on these evaluations, the SIWEC method is employed to determine the relative importance of the criteria, and the resulting weights are subsequently incorporated into the TRUST method to obtain the final ranking of the candidate oxidizers. Accordingly, each table represents the output of a specific stage of the integrated decision-making framework and serves as the input for the subsequent analysis.

In this section, the methodology shared in Section 3 was applied to the problem of evaluating LH_2 oxidizers by following the steps in Figure 1. This study employed a decision-making methodology, used for the first time, to evaluate four oxidizers according to five criteria. To this end, the study aimed to determine decision criteria and alternative oxidizers by collaborating with academic and technical experts experienced in rocket propulsion systems and then to perform step-by-step calculations. Decision criteria and alternatives were identified by utilizing the literature [9,49–53]. The hierarchical structure of the problem is presented in Figure 2.

The decision matrix was constructed using the expert-based scoring procedure described in Section 3.1 (SIWEC, Steps 1–2) and Section 3.2 (TRUST, Step 1). Specifically, domain experts evaluated each candidate oxidizer with respect to the five predefined criteria by following the established scoring procedures. The resulting scores constitute the initial decision matrix used in the subsequent SIWEC weighting and TRUST ranking analy-

ses. Firstly, five experts evaluated the criteria for the oxidizers according to the decision criteria using the linguistic scale and the results are summarized in Table 1.

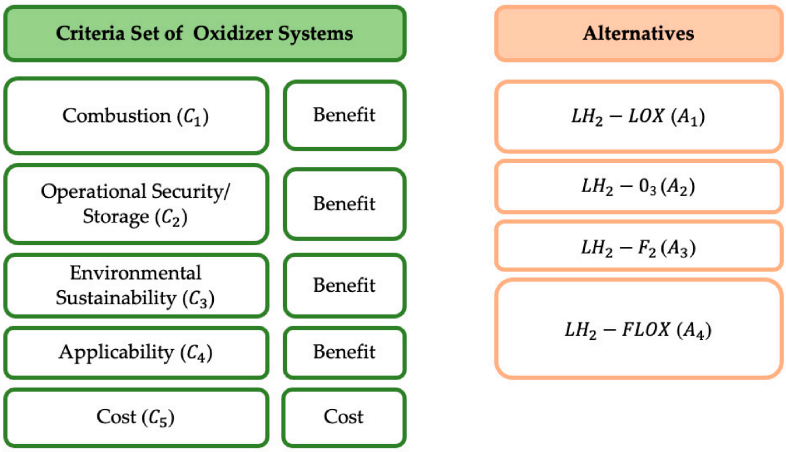

Figure 2. Decision Model.

Table 1. Initial decision-making matrix.

Expert	C_1	C_2	C_3	C_4	C_5
E_1	EG	G	E	P	E
E_2	AG	G	MG	AG	MG
E_3	G	EG	MG	AG	E
E_4	EG	EG	G	EG	MG
E_5	P	VB	EG	MG	B

The assessments made by the 5 experts in Table 1 were converted into numerical expressions as described in step 2 of Section 3.1. These were then normalized using Equation (2), and standard deviations were calculated. The results are presented in Table 2. In this way, the normalized matrix and standard deviations required in the SIWEC method procedures were calculated.

Table 2. Normalized Decision Matrix.

Expert	C_1	C_2	C_3	C_4	C_5	St. Dev.
E_1	0.800	0.875	0.625	1.000	0.833	0.1358
E_2	0.900	0.875	0.750	0.900	1.000	0.0894
E_3	0.700	1.000	0.750	0.900	0.833	0.1193
E_4	0.800	1.000	0.875	0.800	1.000	0.1006
E_5	1.000	0.250	1.000	0.600	0.500	0.3271

Next, the normalized matrix and standard deviations are processed using Equation (3), and the vij values are calculated. Final weights are obtained using Equations (4) and (5). The calculated values are shared in Table 3.

Table 3. Weight Values.

Expert	C_1	C_2	C_3	C_4	C_5
s_{ij}	0.680	0.499	0.657	0.600	0.566
w_{ij}	0.227	0.166	0.219	0.200	0.189

At this stage, the criterion weighting process has been finalized. Since determining criterion weights is one of the most critical phases of multi-criteria decision-making, a systematic weighting procedure based on evaluations by qualified experts was employed to ensure the robustness and reliability of the resulting weights. According to the SIWEC weighting results presented in Table 3, the combustion criterion obtained the highest weight among the five evaluation criteria. This is followed by environmental sustainability and applicability. The criteria with lower weights were identified as cost and operational security, in that order. This result is the direct outcome of the SIWEC weighting procedure applied to the expert evaluations. Therefore, the obtained weights represent the relative importance of the criteria as determined through the adopted decision-making methodology.

Following the determination of the criterion weights, the alternative oxidizers were evaluated within the TRUST framework by incorporating the obtained weights into the decision-making process. To construct the initial decision matrix required for the application of the TRUST method, the same panel of qualified experts was consulted. The aggregated assessments obtained from these experts were then used to construct the initial decision matrix presented in Section 3.2, with the corresponding results reported in Table 4.

Table 4. Aggregated initial decision-making matrix.

Alternatives	C_1	C_2	C_3	C_4	C_5
A_1	6.20	8.40	8.80	9.00	8.20
A_2	5.60	2.60	5.00	2.20	6.20
A_3	8.40	4.60	2.80	4.00	2.60
A_4	8.00	6.20	4.60	5.80	5.00
min	5.6	2.6	2.8	2.2	2.6
max	8.4	8.4	8.8	9	8.2
Sum	28.2	21.8	21.2	21	22
max-min	2.8	5.8	6	6.8	5.6
Product	2333.184	622.8768	566.72	459.36	660.92

The normalization processes, which constitute the most important steps of the method, were performed sequentially using Equations (6)–(12). The normalized matrix values are shared sequentially in Tables 5–8.

Table 5. Normalization Type-1.

Alternatives	C_1	C_2	C_3	C_4	C_5
A_1	0.738	1.000	1.000	1.000	0.317
A_2	0.667	0.310	0.568	0.244	0.419
A_3	1.000	0.548	0.318	0.444	1.000
A_4	0.952	0.738	0.523	0.644	0.520

Table 6. Normalization Type-2.

Alternatives	C_1	C_2	C_3	C_4	C_5
A_1	0.220	0.385	0.415	0.429	0.141
A_2	0.199	0.119	0.236	0.105	0.143
A_3	0.298	0.211	0.132	0.190	0.352
A_4	0.284	0.284	0.217	0.276	0.266

Table 7. Normalization Type-3.

Alternatives	C_1	C_2	C_3	C_4	C_5
A_1	0.214	1.000	1.000	1.000	0.000
A_2	0.000	0.000	0.367	0.000	0.357
A_3	1.000	0.345	0.000	0.265	1.000
A_4	0.857	0.621	0.300	0.529	0.571

Table 8. Normalization Type-4.

Alternatives	C_1	C_2	C_3	C_4	C_5
A_1	0.235	0.331	0.343	0.358	0.324
A_2	0.222	0.149	0.254	0.129	0.281
A_3	0.274	0.237	0.162	0.226	0.147
A_4	0.268	0.284	0.241	0.287	0.248

The four different normalization techniques shared in Tables 5–8 stem from the TRUST method's approach to problem-solving, which is based on moving beyond a single type of normalization process. The merging of these normalized values is achieved using Equation (13), and the h_{ij} values are calculated. To perform this calculation, the calculated values are taken as equal, in accordance with the literature. That is, each normalization process is included in the problem with the same weighting coefficient. The aggregated normalized decision matrix results are presented in Table 9.

Table 9. Aggregated Normalized Decision Matrix.

h_{ij}	C_1	C_2	C_3	C_4	C_5
A_1	0.352	0.679	0.690	0.697	0.195
A_2	0.272	0.144	0.356	0.119	0.300
A_3	0.643	0.335	0.153	0.281	0.625
A_4	0.590	0.482	0.320	0.434	0.401

After combining the normalization processes, an attempt is made to arrive at a satisfaction matrix. Domain experts are involved in the problem for these matrices. This is because the experts need to identify any constraint values remaining between the lower and upper values for each criterion. Identifying these values is a crucial step that distinguishes the TRUST method from other MCDM methods. Unlike conventional methods, the experts are re-involved in the problem, defining new constraints based on needs, as presented in Table 10.

Table 10. Constraint Values of the Criteria.

Constraint	C_1	C_2	C_3	C_4	C_5
LB_j	min	min	min	4	min
UBj	max	8	8.2	max	max

When Table 10 is examined, the upper limits for operational security and environmental sustainability are determined to be lower. The lower limit for applicability was raised due to its inadequacy. Satisfaction matrix calculations are performed by considering the values in Table 10 and paying attention to the direction of the criterion, i.e., whether it is benefit or cost. Benefit criteria use Equations (15)–(17), while cost criteria use Equations (18)–(20) for the calculations. The results are shown in Table 11.

Table 11. Satisfaction Matrix.

f_{ij}	C_1	C_2	C_3	C_4	C_5
A_1	1.000	1.286	1.375	1.000	1.000
A_2	1.000	1.000	1.000	0.667	1.000
A_3	1.000	1.000	1.000	1.867	1.000
A_4	1.000	1.000	1.000	1.000	1.000

After this step, the aggregated normalized decision matrix and the satisfaction matrix are combined using Equation (21). Table 12 contains the results.

Table 12. Constrained Aggregated Normalized Decision Matrix.

y_{ij}	C_1	C_2	C_3	C_4	C_5
A_1	0.352	0.873	0.948	0.697	0.195
A_2	0.272	0.144	0.356	0.080	0.300
A_3	0.643	0.335	0.153	0.525	0.625
A_4	1.000	1.000	1.000	1.000	1.000

The constrained aggregated normalized decision matrix must be integrated with the criterion weights obtained using the SIWEC method. This integration is achieved using Equation (22), and the weighted constrained aggregated normalized decision matrix values are calculated. In the next step, negative ideal solutions are found using Equation (23) and are presented in Table 13.

Table 13. Weighted Constrained Aggregated Normalized Decision Matrix.

g_{ij}	C_1	C_2	C_3	C_4	C_5
A_1	0.080	0.145	0.207	0.139	0.037
A_2	0.062	0.024	0.078	0.016	0.057
A_3	0.146	0.056	0.033	0.105	0.118
A_4	0.134	0.080	0.070	0.087	0.076
NIS	0.062	0.024	0.033	0.016	0.037

To rank the oxidizers, the θ_{ik} and φ_{ik} values are needed. Section 3.2, the Euclidean and Manhattan distances (step 7.1) is calculated using Equations (24) and (25), and the

Lorentz and Pearson distances (step 7.2) is calculated using Equations (26) and (27). The results of these calculations, referred to as the two-stage distance evaluation process in Equations (28) and (29), are summarized in Table 14. The final scores for the Ω_i alternatives in Equation (30) were obtained using the θ_{ik} and φ_{ik} values, along with setting the β parameter to 0.5.

Table 14. Results of the Hybrid SIWEC-TRUST Approach.

Alternatives	E_i	T_i	L_i	P_i	$\sum_{k=1}^{n} \theta_{ik}$	$\sum_{k=1}^{n} \varphi_{ik}$	Ω_i	Rank
A_1	0.246	0.436	0.178	2.475	0.518	0.842	0.680	1
A_2	0.049	0.064	0.027	0.069	−0.265	0.149	−0.058	4
A_3	0.150	0.286	0.120	0.834	0.066	0.204	0.135	2
A_4	0.127	0.274	0.116	0.612	−0.027	0.187	0.080	3

Table 14 shows the basic parameters of the method for oxidizers, the calculated results, and their rankings. According to these results, LH_2-LOX (A_1) is in first place with a clear advantage. LH_2-F_2 (A_3) is in second place. LH_2-FLOX (A_4) is in third place, and LH_2-O_3 (A_2) is clearly in last place. The first results are listed as $A_1 > A_3 > A_4 > A_2$. These findings reflect the distinct physicochemical and operational characteristics of the oxidizers evaluated.

LOX offers a balanced performance profile, with high combustion efficiency, relatively mature storage and transport technologies, operational reliability, and lower environmental and toxicity concerns compared with fluorine-based oxidizers. While F_2 provides extremely high energy performance and combustion reactivity, its severe toxicity, corrosiveness, and transport challenges significantly limit its practical applicability. Similarly, FLOX mixtures combine the high energy potential of fluorine with the relative stability of oxygen but still pose significant safety and operational challenges. In contrast, O_3 possesses strong oxidizing properties; however, its instability, tendency to degrade, and storage complexity negatively impact its applicability in rocket propulsion and overall system reliability [1,5]. The results obtained in this study present the first findings in the literature evaluating LH_2 oxidizers used in rockets within the framework of decision analysis. These findings are largely consistent with the experimental results by Yilmaz et al. [9] which revealed the performance characteristics of oxidizers.

Laboratory testing and physical experiments are indispensable for the comprehensive evaluation of such problems. However, because these processes are both time-consuming and costly, the application of a practical decision-making framework prior to experimental investigations can provide reliable preliminary predictions, thereby assisting decision-makers in identifying the most promising alternatives and optimizing resource allocation.

Overall, the case study demonstrates the applicability of the proposed integrated SIWEC–TRUST framework for the systematic evaluation of candidate oxidizers. The obtained criterion weights and the resulting rankings provide an initial assessment of the relative performance of the evaluated alternatives under the defined decision criteria. Since these findings are derived from expert-based evaluations and methodological computations, it is essential to further examine their robustness. Therefore, additional validation studies, including parameter sensitivity analyses, sensitivity analyses with respect to criterion weights, and comparisons with alternative MCDM methods, are presented in the following section to verify the consistency and reliability of the obtained results.

5. Validation of Results

Although the initial results provide a preliminary assessment, their robustness must be verified through parametric and comparative analyses. Accordingly, this section evaluates the effects of different alpha and beta parameter values through sensitivity analysis and compares the obtained rankings with those generated by several well-established MCDM methods. Table 15 and Figure 3 show the scenarios developed based on the alpha parameter.

Table 15. Approach Scenarios Based on the α Parameter.

Scenario	α_1	α_2	α_3	α_4	Scenario	α_1	α_2	α_3	α_4
S_1	0.25	0.25	0.25	0.25	S_8	0.2	0.1	0.1	0.6
S_2	1	0	0	0	S_9	0.3	0	0	0.7
S_3	0	1	0	0	S_{10}	0.1	0.7	0.1	0.1
S_4	0	0	0	1	S_{11}	0	0	0.5	0.5
S_5	0.33	0.33	0.33	0.00	S_{12}	0	0.5	0	0.5
S_6	0.1	0.2	0.5	0.2	S_{13}	0.5	0.5	0	0
S_7	0.5	0.1	0.1	0.3	S_{14}	0.5	0	0.5	0

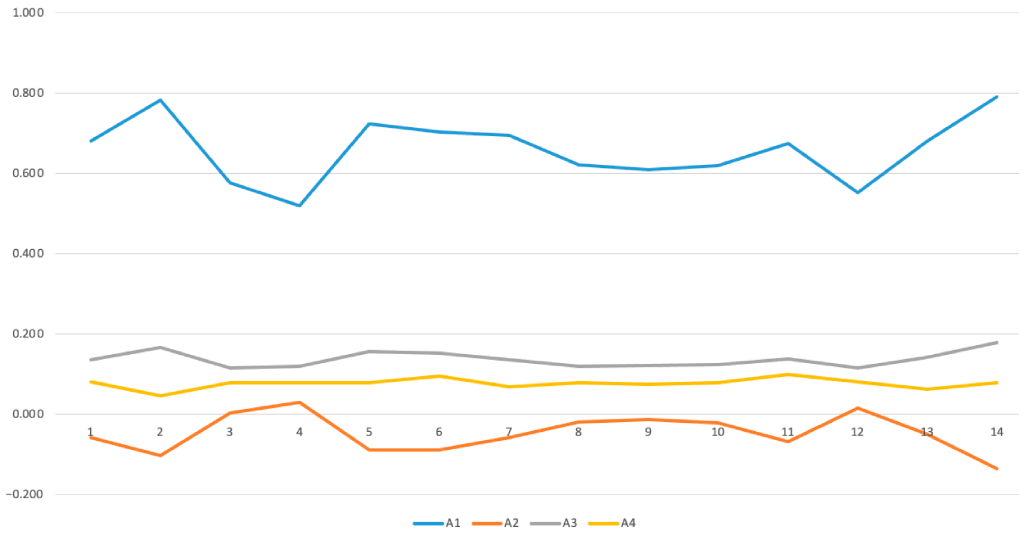

Figure 3. Scores of α Parameters.

Table 15 presents the fourteen validation scenarios together with their corresponding α parameter values. Based on these scenarios, Figure 3 provides a visual comparison between the ranking results obtained under each validation scenario and the initial ranking reported in the Case Study. As illustrated in Figure 3, all validation scenarios produce the same ranking order as the initial analysis, confirming the consistency of the obtained results. Moreover, the figure clearly demonstrates that the LOX alternative consistently remains the highest-ranked oxidizer with a distinct margin over the remaining alternatives, providing additional evidence for the robustness of the proposed framework.

At this point, a second sensitivity analysis based on the beta parameter is necessary. In this context, all possible scenarios were examined using 0.1 increments by varying the beta parameter between 0 and 1. The results obtained are shared in Figure 4.

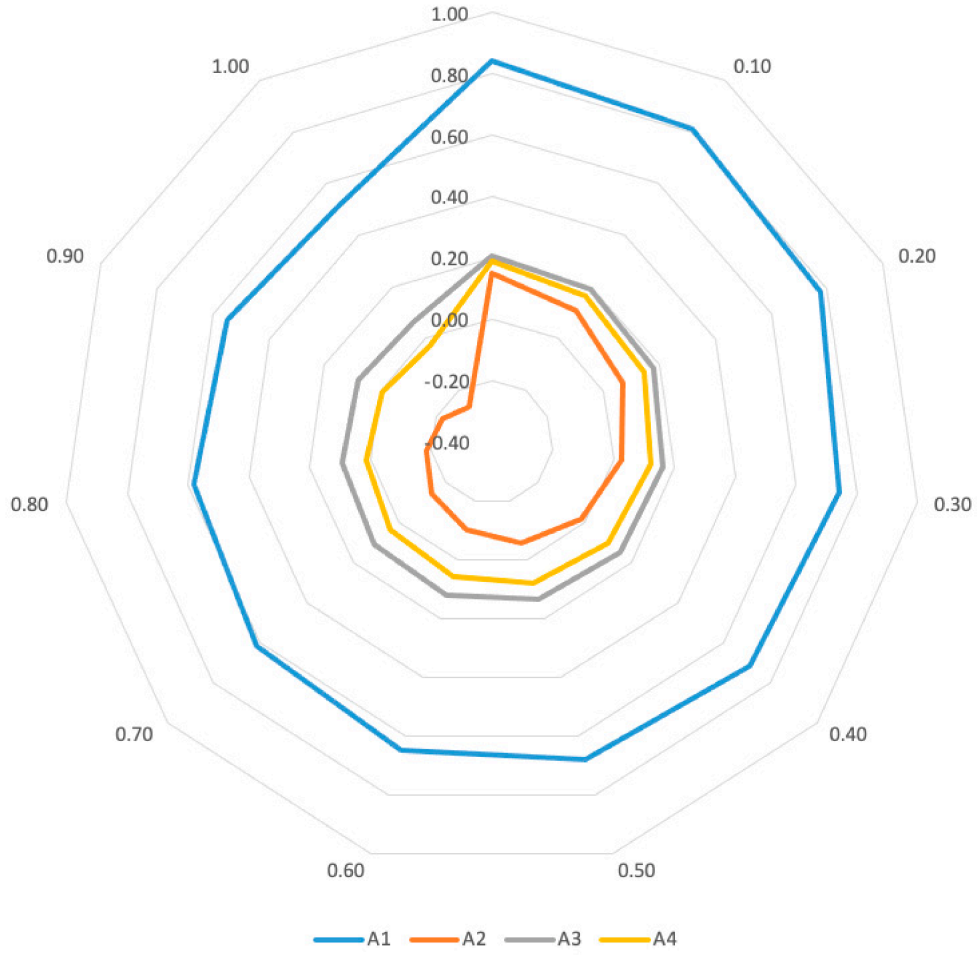

Figure 4. Scores of β Parameters.

Likewise, Figure 4 presents the ranking results corresponding to the β-based validation scenarios. The results demonstrate that variations in the β parameter do not alter the ranking order, further confirming the stability of the proposed framework. While the second- and third-ranked alternatives exhibit very similar performance scores across the examined scenarios, the last-ranked alternative consistently produces the lowest scores. Overall, the α- and β-based sensitivity analyses provide strong evidence that the obtained rankings are highly robust with respect to changes in the aggregation parameters.

However, another aspect of analyses based on the MCDM framework is the possibility of methodological differences. To conduct these reviews, comparative analyses were performed using SAW [54] and WASPAS [55] methods, and the resulting rankings are shared in Figure 5.

Figure 5 clearly shows that there is no change in the first and last alternatives for oxidizers among the methods. The ranking in the analyses is $A_1 > A_4 > A_3 > A_2$. Alternatives A3 and A4 have very close score values. The first alternative is clearly ahead in all analyses.

In addition to the sensitivity analysis performed for the α and β parameters of the TRUST method, further analyses were conducted to evaluate the robustness of the proposed framework with respect to the expert-based criterion weights. Since both the criterion weights and the initial decision matrix are established through expert evaluations, examining the influence of potential variations in these inputs provides an additional assessment of the stability of the obtained rankings. The criterion weights were reversed as point values. That is, the most important criterion in the first position received the score of the

least important criterion in the last position, as shown in Figure 6. The final rankings obtained against these changes are also shared in Figure 7.

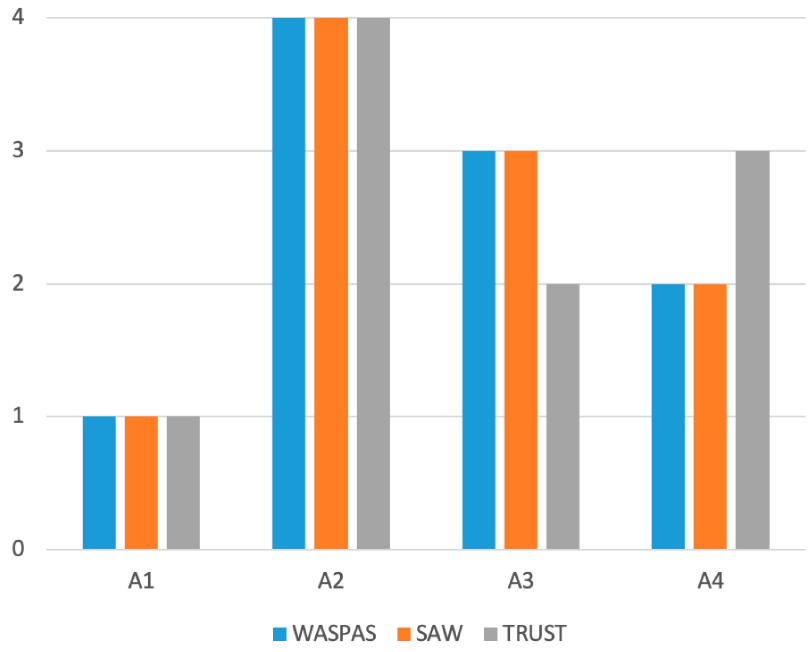

Figure 5. Results of Comparative.

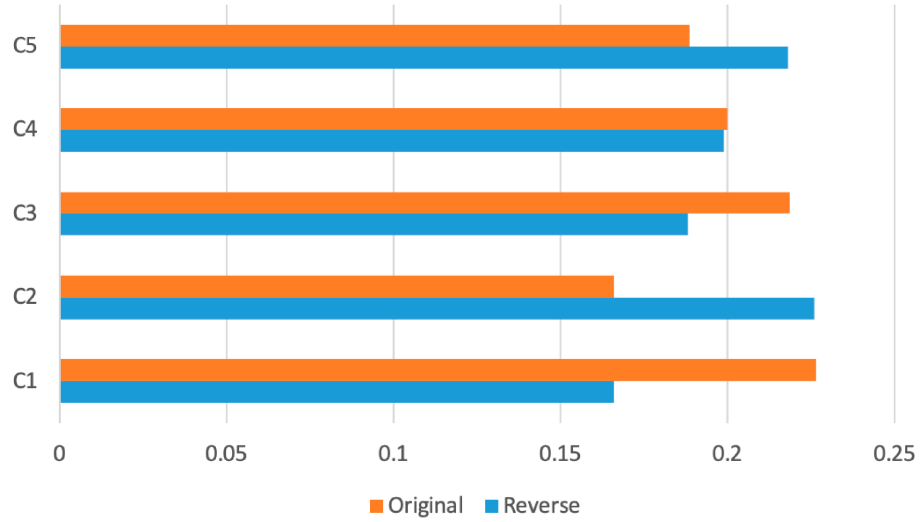

Figure 6. Changes in Weights.

Figure 7 shows the rankings related to the reverse weights, indicated by the index 'r'. The results indicate that the best-performing alternative remains unchanged across all examined scenarios, while the overall ranking exhibits a high degree of consistency. These findings confirm that the proposed integrated SIWEC–TRUST framework produces robust and reliable rankings despite reasonable variations in the expert-based evaluations.

To further validate the proposed MCDM-based evaluation framework, a comparative discussion was conducted with the thermochemical simulation results reported in the literature by Yilmaz et al. [9]. Although the referenced study is based on NASA CEA thermodynamic analysis focusing on performance metrics such as specific impulse under different oxidizer–fuel combinations, while the present study employs a multi-criteria decision-making approach incorporating combustion characteristics, environmental sus-

tainability, cost, applicability, and operational safety, both studies consider the same set of oxidizers (LOX, F_2, FLOX, and O_3) within liquid hydrogen propulsion systems.

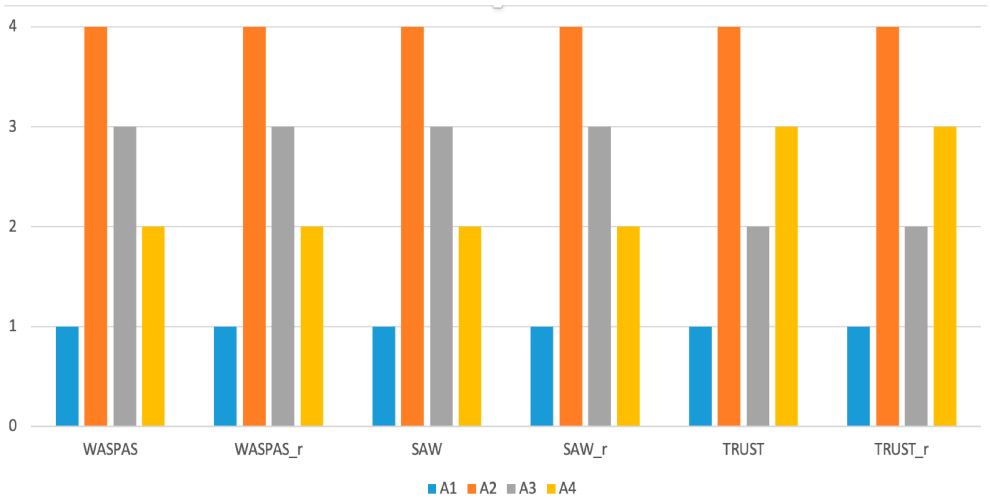

Figure 7. Comparative Rankings with Reverse Weight Results.

Despite the differences in methodological frameworks and evaluation metrics, a strong consistency is observed in the relative feasibility trends of the oxidizers. In both studies, LOX emerges as the most practically viable option due to its operational stability, safety, and established handling characteristics. F_2 and FLOX demonstrate improved theoretical performance but are consistently limited by toxicity, storage complexity, and operational constraints, while O_3 yields the highest theoretical performance in thermodynamic analyses but remains impractical due to instability and safety concerns. These consistent trends indicate that the proposed MCDM framework effectively captures the underlying physical trade-offs between performance and operational feasibility, providing results that are aligned with established thermodynamic behavior in the literature.

Overall, the validation results consistently confirm the robustness of the proposed framework. The α–β parameter sensitivity analysis demonstrated that the ranking remains stable under different aggregation settings, while the sensitivity analysis on criterion weights showed that reasonable variations in expert-derived weights do not alter the leading alternative. In addition, the comparison with established MCDM methods yielded highly consistent rankings, further supporting the reliability of the proposed approach. Across all validation scenarios, LOX remained the highest-ranked oxidizer, indicating that its superiority is not dependent on a specific parameter configuration, weighting scheme, or ranking algorithm but is consistently supported by the integrated evaluation framework. The literature provides information along these lines.

When scenario-based and literature-based results are examined, while LOX-based systems dominate in standard operational and safety-weighted decision environments, ranking results are sensitive to changes in criterion priorities, especially when performance-related criteria such as combustion efficiency are given higher weight than safety and cost. In such alternative scenarios, high-energy oxidizers such as F_2 and O_3 can exhibit better relative performance in purely thermodynamic or mission-specific optimization contexts. However, their practical applicability remains limited due to significant challenges related to toxicity, storage stability, and operational safety. Despite these limitations, fluorine-based oxidizers and ozone can still be important in highly specialized or theoretical propulsion studies, especially in advanced space mission concepts where maximum specific energy is prioritized over operational constraints. Therefore, although these alternatives receive lower rankings in conventional MCDM analyses, their inclusion enables a more

comprehensive evaluation of the trade-offs between performance, practical applicability, and implementation feasibility in rocket propulsion systems.

6. Conclusions

This study proposes a novel MCDM framework for the selection of alternative oxidizers in LH_2-based rocket propulsion systems, addressing a complex and safety-critical engineering problem. The proposed methodology integrates SIWEC-based weight determination with the TRUST aggregation framework, providing a structured and computationally efficient decision-support tool.

The results indicate that the LH_2–LOX combination achieves the highest overall performance among the evaluated alternatives. This outcome is primarily attributed to LOX's balanced characteristics, including high combustion efficiency, technological maturity, operational reliability, and comparatively lower toxicity compared to fluorine-based oxidizers. In contrast, F_2 and FLOX demonstrate high energetic potential but are limited by toxicity, corrosiveness, and operational constraints, while O_3 ranks lowest due to instability and storage challenges. These findings are consistent with established trends reported in the propulsion literature.

The proposed framework offers a flexible basis for complex engineering decision problems and can be extended by incorporating additional performance criteria, alternative oxidizers, and uncertainty-handling approaches. Future work may focus on integrating fuzzy-based MCDM models to better capture expert uncertainty and exploring hybrid approaches with advanced data-driven techniques for large-scale decision environments.

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