Neutrosophic Sets and Systems, Vol. 77, 2025
University of New Mexico

A SuperHyperSoft Framework for Comprehensive Risk Assessment in Energy Projects

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Abstract
Energy projects are rapidly growing and effective risk management and assessment must reduce risks and increase sustainability. But energy projects are complex and have various risks such as environmental risks, regulatory risks, technical risks, and economic risks. This study proposed a multi-criteria decision-making (MCDM) methodology for risk assessment in energy projects to select the lowest energy project risks based on a set of criteria. The MCDM methodology is used under the neutrosophic sets to deal with uncertainty and value information. We used the MABAC method as an MCDM methodology to rank energy projects. We used SuperHyperSoft for the first time, an extension of HyperSoft to treat several criteria and sub-criteria for energy project risks. This study used four criteria and 12 sub-criteria with seven alternatives. A case study was conducted to show the results of the proposed methodology. This study proposed four HyperSoft to select the best alternatives. The results show the technical risks have the highest weights.

Keywords: Risk Management; Energy Projects; Neutrosophic Sets; SuperHyperSoft; MCDM.

1. Introduction

Numerous new lifestyle options and ways to improve our quality of life have been made possible by technological advancements. However, to run these technologies, society needs constant energy, and contemporary civilization prioritizes ensuring its ongoing supply by improving energy efficiency and creating new sources for usage in the future. Given the global economic importance of energy production, ongoing evaluation of both new and current energy sector infrastructure is required for a dependable energy system[1], [2].

As a result, contemporary monitoring techniques that characterize the condition of service and offer insights into system performance are relied upon by academics and operators. By keeping risk levels within reasonable bounds, these techniques assist in lowering expenses, maintenance duration, and undesirable occurrences like accidents in infrastructure and energy projects. Many facets of contemporary life are governed by risk, which is why society has created intricate institutions to assess, discuss, and reduce risk[3], [4].

The probability of undesirable events and project risk can be analyzed using a variety of techniques, such as Bayesian approaches, expert opinion, and classical statistics. Risk analysis techniques are applied in various settings and aid in lowering social inequality, economic disadvantages, environmental impacts of various energy-producing technologies and processes, failures, and accidents. They are frequently included in stakeholders' decision-making processes[5], [6].

One suitable technique for looking into, analyzing, and resolving such issues is multi-criteria decision making (MCDM). The MCDM method considers the preferences of all decision makers when determining the weights (relative importance) of the criteria assessed in the study[7], [8].

One well-known decision-making strategy in literature that has received a lot of attention is the MABAC method. The MABAC is classified as a new MCDM technique and was introduced by Pamucar and Cirovic. The main merits of the MABAC technique are its ease of calculation, the solution's longevity, and the potential number of gains and losses that must be considered to produce a comprehensive outcome. MABAC has recently been used to solve several decision-making issues. In this work, we apply the ideal average notion to improve the MABAC decision-making process, and then we use it to give the experts weights[9], [10].

Formal fuzzy set theory (FST), a decision-making technique that employs a membership function inside the positive range of [0 1], was used to address the problem. Each element of an item is defined by the generated intuitionistic fuzzy set (IFS) both in terms of membership and non-membership. Compared to a fuzzy set, the approach can generate inaccurate information more accurately and consistently. The system's capacity to manage the vague and erratic information that frequently appears in practice is constrained[11], [12].

Single-valued neutrosophic sets (SVNSs) are defined by the notion of neutrosophic sets (NSs), which was first presented in philosophical literature[13], [14]. Using NSs is beneficial for real-world case studies[15], [16]. The components of an object are distributed in SVNSs across the real number space according to their truth, intermediate, and falsity membership degrees[17], [18].

The main contributions of this study are

i. We applied the MCDM methodology for risk management in energy projects to reduce risks in energy projects.
ii. A neutrosophic set is used to deal with uncertainty and vague information.
iii. SuperHyperSoft is used in this study for evaluating the criteria and sub-criteria.
iv. A case study with four criteria and seven alternatives is conducted.

The rest of this study is organized as: Section 2 shows the methodology of this work. Section 3 shows the results of the case study. Section 4 shows the conclusions of this study.

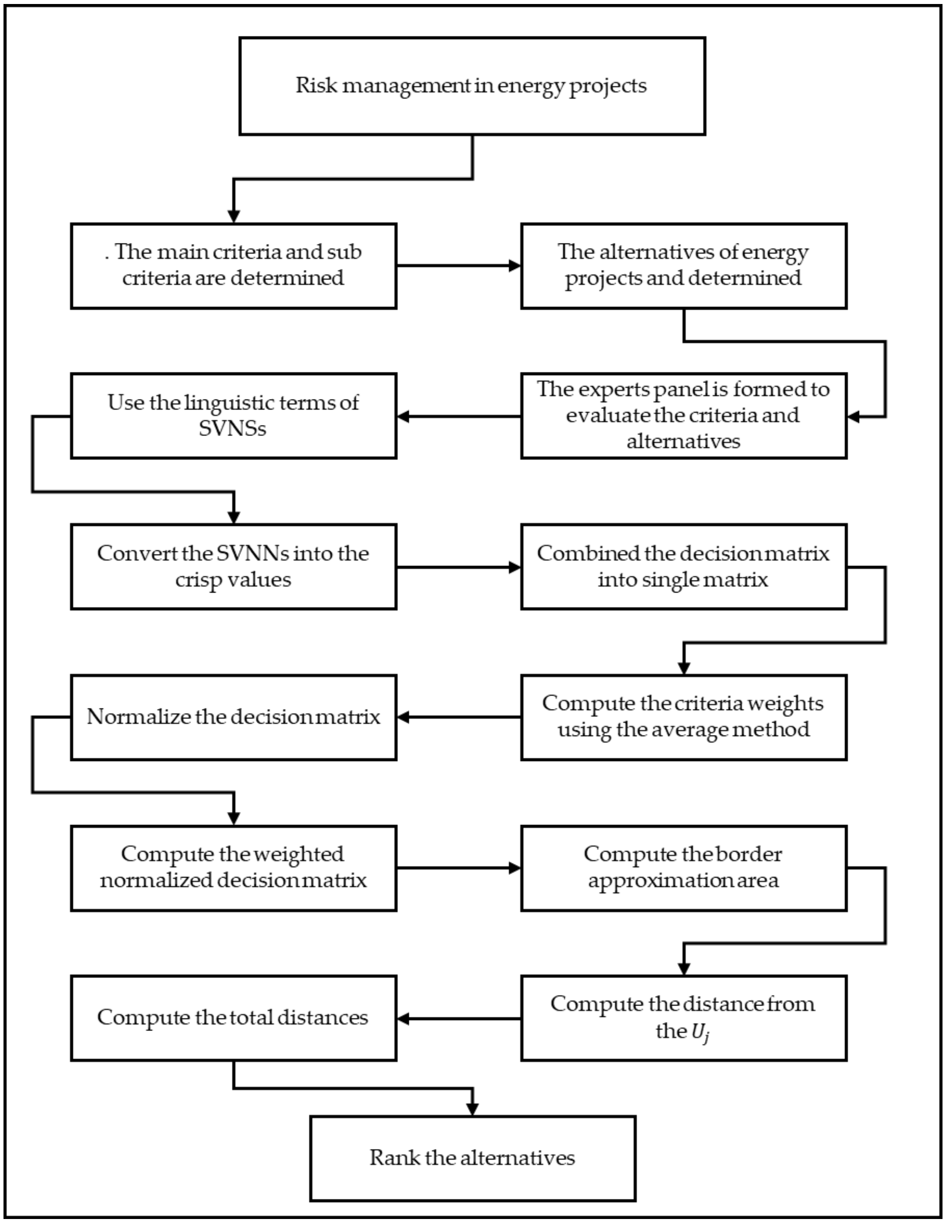

Figure 1. The steps of the SVNS-MABAC with SuperHyperSoft.

2. Ranking the alternatives using SuperHyperSoft and SVNSs-MABAC Method

This section presents the steps of the proposed method to rank the alternatives and obtaining the criteria weights. The MCDM method is used to rank the alternatives. SuperHyperSoft is used to compute and employ the power set of criteria to attain the best alternatives. The SVNSs are used with the MABAC method to rank the options. Figure 1 shows the steps of the SVNSs-MABAC with SuperHyperSoft.

SuperHyperSoft (SH)

SH is a method an extension of HyperSoft set. It is used to determine the best values of criteria and sub criteria. Let the universe set $Y = \{A_1, A_2, \dots, A_m\}$ and $\mathrm{P}(Y)$ is the powerset of Y as $C_1, \dots., C_n$ is a criterion while the A refers to the alternatives[19], [20].

$P(C_1), P(C_2)\ and\ P(C_3)$ are the powerset of a set of criteria

Let $Q: P(C_1) \times P(C_2) \times P(C_3) \rightarrow P(C)$

$$P(C_1) \times P(C_2) \times P(C_3) = \left\{\{\{C_{11}\}, \{C_{12}\}, \{C_{11}, C_{12}\}\}\right\} \times \left\{\{\{C_{21}\}, \{C_{22}\}, \{C_{21}, C_{22}\}\}\right\} \times \left\{\{\{C_{31}\}, \{C_{32}\}, \{C_{31}, C_{32}\}\}\right\}$$

$$P(C_1) \times P(C_2) \times P(C_3) = \left\{ \begin{matrix} R(C_{11}, C_{21}, C_{31}); R(C_{11}, C_{21}, C_{32}); R(C_{11}, C_{21}, C_{33}) \\ R(C_{11}, C_{21}, \{C_{31}, C_{32}\}); R(C_{11}, C_{21}, \{C_{31}, C_{33}\}); R(C_{11}, C_{21}, \{C_{32}, C_{32}\}) \\ R(C_{11}, C_{21}, \{C_{31}, C_{32}, C_{33}\}); R(C_{11}, C_{22}, C_{31}); R(C_{11}, C_{22}, \{C_{31}, C_{32}, C_{33}\}) \end{matrix} \right\}$$

SVNSs-MABAC Method

1. The main criteria and sub-criteria are determined to evaluate the alternatives

2. The alternatives to energy projects and determined.

3. The expert panel is formed to evaluate the criteria and alternatives.

4. Use the linguistic terms of SVNSs to evaluate the criteria and alternatives and build the decision matrix.

5. Convert the SVNNs into the crisp values.

6. Combined the decision matrix into a single matrix

7. Compute the criteria weights using the average method.

8. Normalize the decision matrix

$$N_{ij} = \frac{x_{ij} - \min x_i}{\max x_i - \min x_i} \tag{1}$$

$$N_{ij} = \frac{x_{ij} - \max x_i}{\max x_i - \min x_i} \tag{2}$$

9. Compute the weighted normalized decision matrix.

$$T_{ij} = W_j + W_j * N_{ij} \tag{3}$$

10. Compute the border approximation area.

$$U_j = \left(\prod_{i=1}^{m} T_{ij}\right)^{\left(\frac{1}{m}\right)} \tag{4}$$

11. Compute the distance from the U_j

$$D_{ij} = T_{ij} - U_j \tag{5}$$

12. Compute the total distances.

$$S_i = \sum_{j=1}^{n} D_{ij} \tag{6}$$

13. Rank the alternatives.

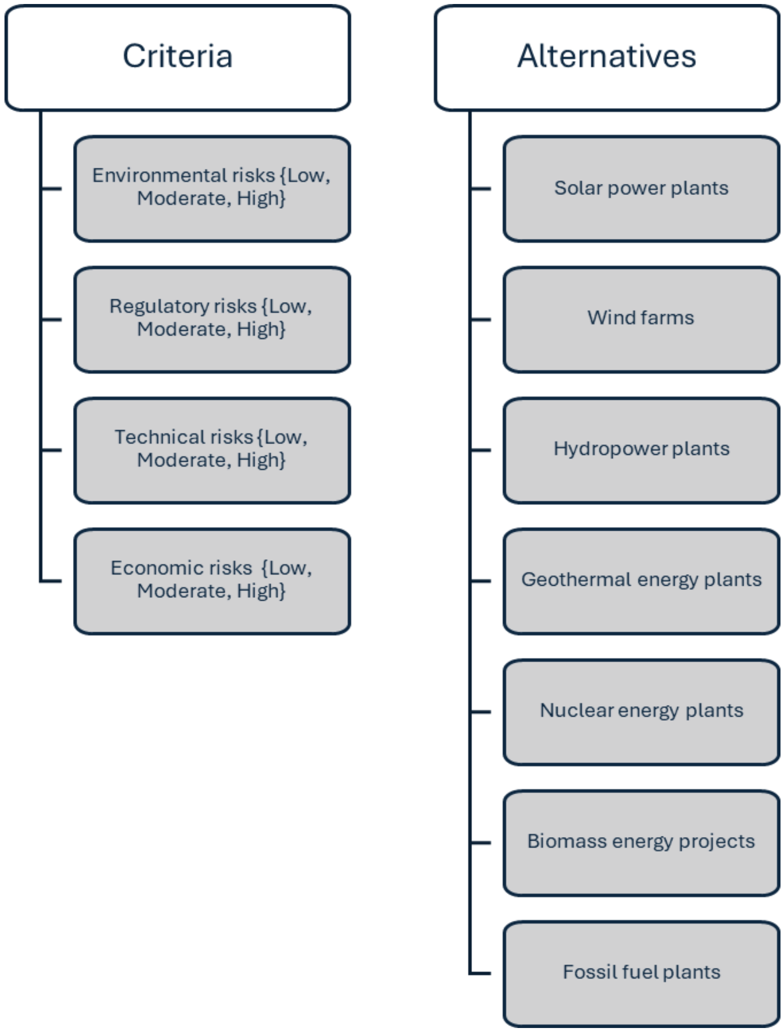

Figure 2. The energy projects criteria.

3. Results

This section shows the results of the proposed methodology for risk assessment in energy projects to reduce risks and select the lowest energy project risks.

1. We select four main criteria and 12 sub-criteria as shown in Figure 2.

2. We select seven energy projects to select the lowest projects at risk.

3. Three experts are invited to evaluate the criteria and alternatives.

4. Three experts use seven linguistic terms to evaluate the criteria and alternatives to build the decision matrix as shown in Table 1.

5. Then we used the score function to obtain the crisp values.

6. Then we combined the decision matrix.

Table 1. Three decision matrices.

	C_1	**C_2**	**C_3**	**C_4**
A_1	(0.1,0.8,0.9)	(0.2,0.7,0.8)	(0.3,0.6,0.7)	(0.5,0.5,0.5)
A_2	(0.6,0.4,0.3)	(0.9,0.2,0.1)	(0.7,0.3,0.2)	(0.6,0.4,0.3)
A_3	(0.7,0.3,0.2)	(0.6,0.4,0.3)	(0.5,0.5,0.5)	(0.3,0.6,0.7)
A_4	(0.9,0.2,0.1)	(0.9,0.2,0.1)	(0.6,0.4,0.3)	(0.2,0.7,0.8)
A_5	(0.1,0.8,0.9)	(0.1,0.8,0.9)	(0.5,0.5,0.5)	(0.1,0.8,0.9)
A_6	(0.2,0.7,0.8)	(0.2,0.7,0.8)	(0.3,0.6,0.7)	(0.9,0.2,0.1)
A_7	(0.3,0.6,0.7)	(0.5,0.5,0.5)	(0.6,0.4,0.3)	(0.7,0.3,0.2)
	C_1	C_2	C_3	C_4
A_1	(0.1,0.8,0.9)	(0.2,0.7,0.8)	(0.5,0.5,0.5)	(0.5,0.5,0.5)
A_2	(0.6,0.4,0.3)	(0.9,0.2,0.1)	(0.6,0.4,0.3)	(0.6,0.4,0.3)
A_3	(0.7,0.3,0.2)	(0.5,0.5,0.5)	(0.3,0.6,0.7)	(0.3,0.6,0.7)
A_4	(0.5,0.5,0.5)	(0.5,0.5,0.5)	(0.2,0.7,0.8)	(0.2,0.7,0.8)
A_5	(0.6,0.4,0.3)	(0.6,0.4,0.3)	(0.6,0.4,0.3)	(0.1,0.8,0.9)
A_6	(0.3,0.6,0.7)	(0.3,0.6,0.7)	(0.3,0.6,0.7)	(0.9,0.2,0.1)
A_7	(0.2,0.7,0.8)	(0.2,0.7,0.8)	(0.2,0.7,0.8)	(0.7,0.3,0.2)
	C_1	C_2	C_3	C_4
A_1	(0.1,0.8,0.9)	(0.2,0.7,0.8)	(0.6,0.4,0.3)	(0.6,0.4,0.3)
A_2	(0.6,0.4,0.3)	(0.9,0.2,0.1)	(0.7,0.3,0.2)	(0.7,0.3,0.2)
A_3	(0.7,0.3,0.2)	(0.6,0.4,0.3)	(0.9,0.2,0.1)	(0.9,0.2,0.1)
A_4	(0.9,0.2,0.1)	(0.7,0.3,0.2)	(0.1,0.8,0.9)	(0.1,0.8,0.9)
A_5	(0.1,0.8,0.9)	(0.9,0.2,0.1)	(0.7,0.3,0.2)	(0.9,0.2,0.1)
A_6	(0.2,0.7,0.8)	(0.1,0.8,0.9)	(0.9,0.2,0.1)	(0.1,0.8,0.9)
A_7	(0.3,0.6,0.7)	(0.5,0.5,0.5)	(0.1,0.8,0.9)	(0.7,0.3,0.2)

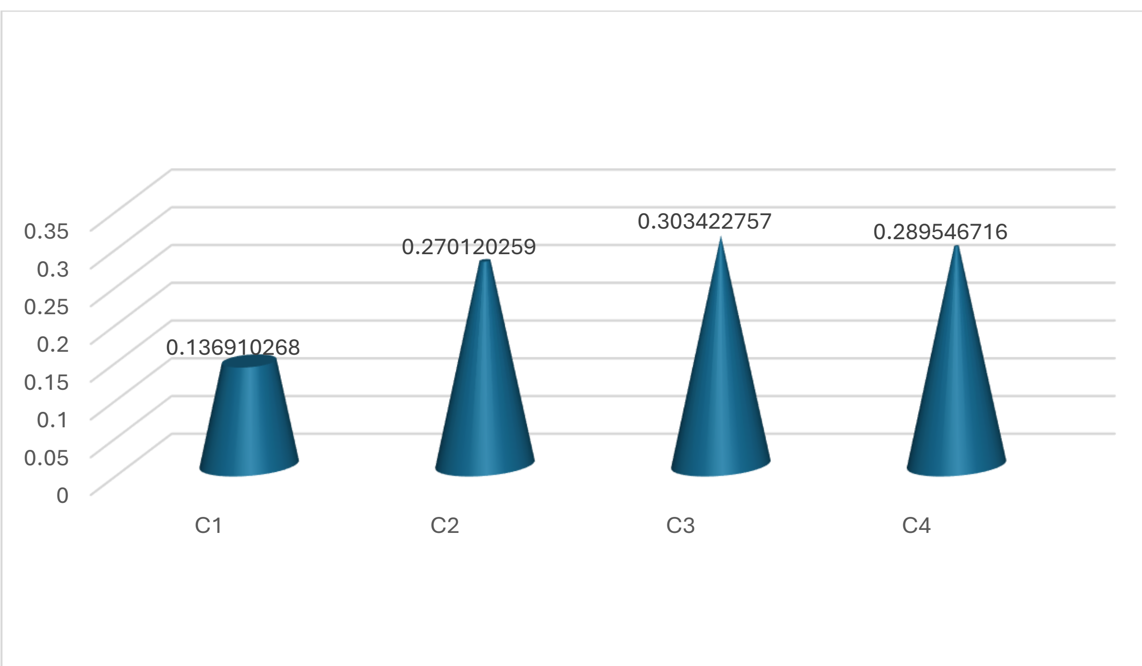

Figure 3. The criteria weights.

7. Figure 3 shows the criteria for weights.

Based on the SH we can propose a set of sub-criteria to rank the alternatives: Moderate

Let $R\left(F(\{High, Low\}, \{High, Low\}, \{High, \text{moderate}, Low\}, \{High, \text{moderate}, Low\})\right)$ and we select the

$R\left(F(\{High, Low\}, \{High, Low\}, \{High\}, \{High\})\right)$ then we have four propositions to express the HyperSoft set

Proposition 1: High, High, High, High

Proposition 2: High, Low, High, High

Proposition 3: Low, High, High, High

Proposition 4: Low, Low, High, High

Based on Proposition 1

- Three experts were invited to build three decision matrices, and then we combined them.
- We normalize the decision matrix as shown in Table 2.
- Then we compute the weighted normalized decision matrix as shown in Table 3.
- Then we Compute the border approximation area.
- Then we compute the distance from the U_j
- Then we compute the total distances.
- Then we Rank the alternatives as shown in Figure 4.

Table 2. The normalized decision matrix

	C1	**C2**	**C3**	**C4**
A1	0	0	0.424242	0.645833
A2	0.818181817	1	1	0.875
A3	0.981818181	0.561404	0.636364	0.583333
A4	1	0.736842	0	0
A5	0.272727272	0.491228	0.787879	0.333333
A6	0.218181818	4.38E-17	0.484848	0.791667
A7	0.272727272	0.280702	0	1

Table 3. The weighted normalized decision matrix

	C1	**C2**	**C3**	**C4**
A1	0.136910268	0.27012	0.432148	0.476546
A2	0.24892776	0.540241	0.606846	0.5429
A3	0.271331259	0.421767	0.49651	0.458449
A4	0.273820537	0.469156	0.303423	0.289547
A5	0.174249432	0.402811	0.542483	0.386062
A6	0.1667816	0.27012	0.450537	0.518771
A7	0.174249432	0.345943	0.303423	0.579093

Based on Proposition 2

- Three experts were invited to build three decision matrices, and then we combined them.
- We normalize the decision matrix as shown in Table 4.
- Then we compute the weighted normalized decision matrix as shown in Table 5.
- Then we Compute the border approximation area.
- Then we compute the distance from the U_j
- Then we compute the total distances.
- Then we Rank the alternatives as shown in Figure 4.

Table 4. The normalized decision matrix

	C1	**C2**	**C3**	**C4**
A1	0	0	0.424242	0.645833
A2	0.818182	1	1	0.875
A3	0.981818	0.487805	0.636364	0.583333
A4	1	0.731707	0	0
A5	0.272727	0.390244	0.787879	0.333333
A6	0.218182	0.146341	0.484848	0.791667
A7	0.272727	0.195122	0	1

Table 5. The weighted normalized decision matrix

	C1	**C2**	**C3**	**C4**
A1	0.13691	0.27012	0.432148	0.476546
A2	0.248928	0.540241	0.606846	0.5429
A3	0.271331	0.401886	0.49651	0.458449
A4	0.273821	0.467769	0.303423	0.289547
A5	0.174249	0.375533	0.542483	0.386062
A6	0.166782	0.30965	0.450537	0.518771
A7	0.174249	0.322827	0.303423	0.579093

Based on Proposition 3

- Three experts were invited to build three decision matrices, and then we combined them.
- We normalize the decision matrix as shown in Table 6.
- Then we compute the weighted normalized decision matrix as shown in Table 7.
- Then we Compute the border approximation area.
- Then we compute the distance from the U_j
- Then we compute the total distances.
- Then we Rank the alternatives as shown in Figure 4.

Table 6. The normalized decision matrix

	C1	**C2**	**C3**	**C4**
A1	0	0	0.424242	0.645833
A2	0.519231	1	1	0.875
A3	0.634615	0.561404	0.636364	0.583333
A4	1	0.736842	0	0
A5	0.230769	0.491228	0.787879	0.333333
A6	0.538462	4.38E-17	0.484848	0.791667
A7	0.538462	0.280702	0	1

Table 7. The weighted normalized decision matrix

	C_1	C_2	C_3	C_4
A_1	0.13691	0.27012	0.432148	0.476546
A_2	0.207998	0.540241	0.606846	0.5429
A_3	0.223796	0.421767	0.49651	0.458449
A_4	0.273821	0.469156	0.303423	0.289547
A_5	0.168505	0.402811	0.542483	0.386062
A_6	0.210631	0.27012	0.450537	0.518771
A_7	0.210631	0.345943	0.303423	0.579093

Based on Proposition 4

- Three experts were invited to build three decision matrices, and then we combined them.
- We normalize the decision matrix as shown in Table 8.
- Then we compute the weighted normalized decision matrix as shown in Table 9.
- Then we Compute the border approximation area.
- Then we compute the distance from the U_j
- Then we compute the total distances.
- Then we Rank the alternatives as shown in Figure 4.

Table 8. The normalized decision matrix

	C_1	C_2	C_3	C_4
A_1	0	0.045455	0.424242	0.645833
A_2	1	1	1	0.875
A_3	0.911765	0.386364	0.636364	0.583333
A_4	0.735294	0.477273	0	0
A_5	0.117647	0	0.787879	0.333333
A_6	0.588235	0.363636	0.484848	0.791667
A_7	0.470588	0.386364	0	1

Table 9. The weighted normalized decision matrix

	C_1	C_2	C_3	C_4
A_1	0.13691	0.282398	0.432148	0.476546
A_2	0.273821	0.540241	0.606846	0.5429
A_3	0.26174	0.374485	0.49651	0.458449
A_4	0.23758	0.399041	0.303423	0.289547
A_5	0.153017	0.27012	0.542483	0.386062
A_6	0.217446	0.368346	0.450537	0.518771
A_7	0.201339	0.374485	0.303423	0.579093

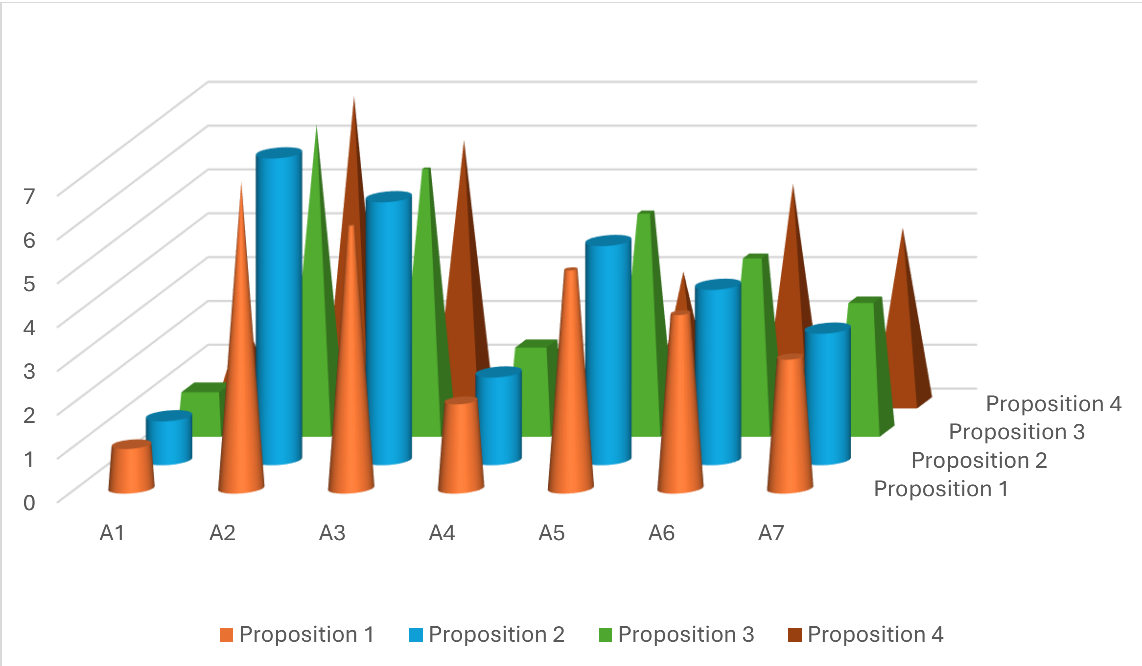

Figure 4. The rank of alternatives.

4. Conclusions

This study proposed an MCDM method for risk assessment and management in energy projects. Energy projects are complex and have various risks. So, we proposed a framework for ranking these risks and selecting the best energy projects that have fewer risks to reduce risks and increase sustainability. The MABAC method was used to rank the alternatives. The MABAC method is employed under the neutrosophic sets to deal with uncertainty and vague information. The proposed method is introduced with SuperHyperSoft to treat the criteria and alternatives. Four main criteria and seven alternatives are used to select the best alternatives. Three experts have evaluated the criteria and alternatives. Four HyperSoft are introduced to select the best alternatives. The criteria weights are determined under the verge method. The results show the technical risks have the highest weights.

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Received: Aug 09, 2024. **Accepted**: Nov 23, 2024