SELECTION OF BEST ENERGY STORAGE TECHNOLOGY USING ELECTRE III-BWM METHOD UNDER LINGUISTICS NEUTROSOPHIC FUZZY APPROACH

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Abstract

Renewable energy provides more environmentally friendly sources of energy, which reduces the demand for fossil fuels and is therefore necessary to reach zero emissions of carbon. But the need for systems that are capable of capturing and storing this energy is expanding as the world gets a growing amount of electricity from these forms of renewable energy. In present-day society, renewable energy storage is widely used, and governments are concentrating on developing suitable storage technologies together with a plan for upcoming energy storage reduction. Energy storage technologies have been proposed as potential solutions for this issue due to their ability to store energy and lower energy consumption. Aspects of technology, economy, society, and environment are the four main criteria used in this study to examine different energy storage techniques. The most effective strategy was identified in this paper. In this study, we use the ELECTRE-III approach to suggest the optimal storage technology under the linguistic neutrosophic fuzzy set. Finally, a numerical example of this area of study is provided. A comparison and sensitivity analysis are shown for the effectiveness of the proposed method.

Keywords: Neutrosophic Fuzzy Set, Linguistic Neutrosophic Fuzzy Set, ELECTRE-III, BWM, Renewable energy storage technology.

1. Introduction

Energy, which is frequently defined as the ability to complete a task, is a crucial concept for both the long-term development of countries and the ongoing growth of the human race. Energy is so vital to the global economic and social progress of the world that an extensive amount of study is focused on guaranteeing its afford-ability, availability, and stability. Renewable energy (RE) and non-renewable energy (NRE) alternatives or sources are the two categories into which types of energy can be separated. Natural sources of energy include wind, sun, hydro, geothermal, biomass, and waves, while NRE sources include coal, oil, nuclear energy, and natural gas. As they emit fewer greenhouse gases (GHGs) than fossil fuels, renewable energy sources (RES) are better for the environment. However, as a result of increasing population and industrialization, there is an increase in worldwide energy demand. To meet this growing need, RES are currently thought to be viable solutions. Nevertheless, these energy sources exhibit unpredictable and intermittent properties. Energy storage technologies (ESTs) were subsequently created to ensure the availability of energy by allowing the storage of extra energy and its utilization when required.

The five kinds of energy technology preservation, often known as alternatives, are electrical, mechanical, chemical-based, electrochemical, and thermo [1, 15].

In the twenty-first century, conventional carbon-based fuels, including coal, oil, and natural gas, are the most widely used sources of energy. Conventional agriculture's fossil fuel consumption has fueled economic growth worldwide, but it has also resulted in significant environmental issues. The primary source of the greenhouse effect is the massive amount of CO_2 produced from the burning of fossil fuels. As a result, there has been a considerable advancement in the development of new and renewable energy sources with plentiful resources and minimal adverse effects on the environment. The creation of RE is essential to lowering CO_2 emissions and resolving environmental issues. It is also a widely accepted solution to resource exhaustion and air pollution. Meanwhile, there have been obstacles and restrictions in the way of the growth of clean energy. The production of energy based on sustainable sources is reliant on the erratic and transient demand for natural assets. These features impact the security and reliability of the power grid, in addition to making it challenging to change and regulate the production of energy [2, 3]. Thus, energy storage is becoming a crucial factor in the advancement of renewable energy sources.

An important idea that makes it possible to assess options in light of numerous competing criteria for a decision-making (DM) challenge is multi-criteria decision-making (MCDM). When the MCDM process is complete, the goal is to have chosen the best option from a variety of options. Despite conventional and fuzzy MCDM techniques being used to achieve this goal, fuzzy models offer a way to deal with the ambiguity inherent in human perspectives, leading to more realistic and feasible outcomes [4]. It is evident that choosing the best EST is an MCDM problem since evaluating various ESTs requires the realization of a thorough assessment in terms of these criteria, and there are numerous competing criteria, including technical, economic, environmental, and social ones. As a result, it makes sense to combine MCDM techniques with Zadeh's fuzzy set theory (FST), which allows for the modeling of human judgment uncertainties during MCDM problem analysis. Furthermore, some recently created extensions of conventional fuzzy sets, like intuitionistic, Pythagorean fuzzy sets, hesitant, and type-2, are useful in addressing vagueness in the MCDM process [5, 6]. The energy storage problem is being solved in this work by employing linguistic neutrosophic fuzzy numbers.

The truth, indeterminacy, and falsity linguistic term values are expressed independently by three specific linguistic variables, l_T, l_I, and l_F, using a linguistic neutrosophic fuzzy number. Researchers have recently focused more on the fascinating study areas of making decisions in linguistic circumstances. Zadeh [24] highlighted how fuzzy logic makes use of language characteristics. To overcome the difficulties in using linguistic information to make judgments, Herrera and Herrera-Viedma [25] and Herrera et al. [26] created linguistic decision studies. According to Chen et al. [27], the linguistic intuitionistic fuzzy number (LIFN) is defined as $s = (l_a, l_b)$, where l_a and l_b represent the linguistics characteristics of membership, and non-membership, respectively. The MAGDM process is then developed using LIFNs. For MADM, Liu and Wang [28] created improved LIFN aggregation methods. The LIFN elucidates the linguistic details of both truth and falsehood degrees and is evidently composed of two linguistic variables, l_a and l_b.

However, LIFNs are not able to describe inconsistent and unclear language data. An integral part of an SVNS, a single-valued neutrosophic number (SVNN) [29] can convey degrees of truth, indeterminacy, and untruth; it also reveals details that are insufficient, inconsistent, and not resolved in SVNN instead of linguistic data. As a result, unlike linguistic variables, it is unable to describe linguistic formation in a linguistic issue of decision-making. Ye [30] introduced the SVNLN, which consists of an SVNN and a syntactic variable. The SVNN indicates the consistency of the given linguistic variable, while the linguistic factor represents the decision-maker's assessment of an object under examination. Within the context of the previously indicated concept, it is necessary to propose an interpretation of a linguistic neutrosophic number (LNN), which is expressed as an LNN $e =< l_4, l_2, l_3 >$. It is clear that LIFN and SVNLN cannot communicate such verbal assessing values; on the other hand, LNN, which combines SVNN and

LIFN into LNN, might just be the minimal language environment. As a result, LNN needs to be used to resolve linguistic DM problems with erratic and indeterminate linguistic information as well as to express incomplete and unresolved linguistic information that corresponds to human fuzzy reasoning regarding complex problems, particularly certain qualitative attribute assessments [31, 32, 33]. As a result, the best appropriate option under a linguistic neutrosophic fuzzy environment has been identified, and ESTs have been assessed employing a fuzzy MCDM approach using the LNFNs technique in this study.

2. Literature Review

Many researchers have identified suitable energy storage methods, which we address in this section on energy storage systems. Examine the energy storage technologies from the standpoint of energy security, as presented by Azzuni and Breyer [7]. Gao and Lu [8] are examining the latest developments in this developing field, particularly the novel ideas, methods, and uses of machine learning technologies for widely utilized energy storage systems and gadgets. The dual-hesitant Pythagorean fuzzy linguistic term sets are defined by Liu and Du [9], who also suggest an MCDM framework for choosing renewable energy storage technologies. Kumar et al. [10] provide a review of different MCDM approaches, advancements made when comparing the techniques to renewable energy usage, and potential future developments. Chen et al. [11] explored Prospect Theory and PROMETHEE in the selection of renewable energy sources. Pamucar et al. [12] proposed a Dombi weighted geometric averaging operator and MAIRCA model under hybrid trapezoidal neutrosophic fuzzy numbers, and then evaluated and rated the available energy storage technology solutions in accordance with the selected specifications. Barin et al. [13] found the most appropriate energy storage system consistent with a power quality priority. Rahman [14] reviews the techno-economic and ecological evaluations of thermal energy, chemical in nature, electro-chemical, and mechanical procedures in order to provide a review of current advancements and create a pertinent database for expenses and emissions. The various energy storage systems, with Aneke and Wang's [16] investigation focusing primarily on the storage system. Ren [17] was working on creating a multi-attribute decision-analysis framework to prioritize energy storage solutions based on sustainability. Large-scale storage of energy systems of life cycle consumption of energy and the release of greenhouse gases were suggested by Denholm and Kulcinski [18].

Further MCDM methods have been used for evaluating the EST problem. Table 1 presents the MCDM methods used and the suggested option.

Table 1: *MCDM methods used various researchers*

Author's	MCDM methodology	Problem
Sengul et al. (2015) [19]	TOPSIS	Renewable energy
Ozkan et al. (2015) [20]	AHP-TOPSIS	Selection of Energy Storage Alternatives
Zhang et al. (2019) [21]	fuzzy MULTIMOORA	Assessment of the energy storage technologies
Ren (2018) [22]	Fuzzy IAHP	Development of renewable energy
Colak and Kaya (2020) [23]	CRITIC-MOORA, TOPSIS, COPRAS	Hydropower

Using various MCDM models, the evaluated research primarily sought to identify the best choices for renewable energy storage technologies, utilizing the constantly evolving MCDM techniques that are essential to the field of sustainable energy management. Because different approaches offer different solutions, it is necessary to perform a thorough, country-specific analysis in order to successfully handle the issue. There is yet unrealized potential for combining ELECTRE III and the Best-Worst Method (BWM) to enhance EST selection. The ability of Linguistic Neutrosophic Fuzzy Sets (LNFSs) to represent not only truth and falsehood but also neutrality provides a strong model for handling difficult decision-making situations; however, more research is needed to determine how well LNFSs integrate with the suggested methodology. The amalgamation of these elements has the potential to greatly expand its relevance in various domains and enhance the effectiveness of decision-making. As such, this study aims to establish a general framework for determining which energy storage technology is most suitable, taking into account social, economic, and technological factors.

3. Preliminaries

Definition 3.1. A Neutrosophic fuzzy set (NFS) ω on R:

$$\omega = \{(o, p_\omega(o), q_\omega(o), r_\omega(o)) : o \in R\} \tag{1}$$

where $p_\omega(o), q_\omega(o), r_\omega(o) \in [0,1], 0 \leq p_\omega(o) + q_\omega(o) + r_\omega(o) \leq 3$ for all $o \in R$, $p_\omega(o)$, $q_\omega(o)$, $r_\omega(o)$ are degrees of membership, indeterminacy and non-membership, respectively.

Definition 3.2. Let $N = n_0, n_1, ..., n_t$ be a LTS with odd cardinality $f + 1$. If $e =< n_a, n_b, n_c >$ is defined for $n_a, n_b, n_c \in N$ and $a, b, c \in [0, f]$, where n_a, n_b, and n_c represent the trueness, indeterminacy, and falseness level by linguistic terms and e is called an LNN.

Definition 3.3. Let $u =< n_a, n_b, n_c >$, $u_1 =< n_{a_1}, n_{b_1}, n_{c_1} >$ and $u_2 =< n_{a_2}, n_{b_2}, n_{c_2} >$ be three LNNs in N and $c > 0$, then

- $u_1 \oplus u_2 =< n_{a_1}, n_{b_1}, n_{c_1} > \oplus < n_{a_2}, n_{b_2}, n_{c_2} >=< n_{a_1+b_2-\frac{a_1 a_2}{f}}, n_{\frac{b_1 b_2}{f}}, n_{\frac{c_1 c_2}{f}} >$
- $u_1 \otimes u_2 =< n_{a_1}, n_{b_1}, n_{c_1} > \otimes < n_{a_2}, n_{b_2}, n_{c_2} >=< n_{\frac{a_1 a_2}{f}}, n_{a_1+a_2-\frac{a_1 a_2}{f}}, n_{\frac{c_1 c_2}{f}} >$
- $\phi u = \phi < n_a, n_b, n_c >=< n_{f-f(1-\frac{a}{f})^\phi}, n_{f(\frac{b}{f})^\phi}, n_{f(\frac{c}{f})^\phi} >$
- $u^\phi =< n_a, n_b, n_c >^\phi =< n_{f(\frac{a}{f})^\phi}, n_{f(\frac{b}{f})^\phi}, n_{f-f(1-\frac{c}{f})^\phi} >$

Definition 3.4. Let $e =< n_a, n_b, n_c >$ be an LNN in N. Then the score and accuracy functions of e is given below:

$$S(e) = \frac{(2f + a - b - c)}{3f} \text{ for } S(e) \in [0,1] \tag{2}$$

$$A(e) = \frac{(a - c)}{f} \text{ for } F(e) \in [-1,1] \tag{3}$$

Definition 3.5. Let $u_1 =< s_{a_1}, s_{b_1}, s_{c_1} >$ and $u_2 =< s_{a_2}, s_{b_2}, s_{c_2} >$ be any two LNNs, and let f^* be a linguistic scale function $t \geq 0$. The generalized distance measure of a_i & a_j is

$$d(u_1, u_2) = \left(\frac{1}{3}(|f^*(s_{a_1} - f^*(s_{a_2}))|^t + |f^*(s_{b_1} - f^*(s_{b_2}))|^t + |f^*(s_{c_1} - f^*(s_{c_2}))|^t)^t\right) \tag{4}$$

where $t = 1$ or $t = 2$, and the above equation is reduced to the Hamming distance or the Euclidean distance, respectively.

4. Proposed Method

Let $H = (h_1, h_2, ..., h_t)$ be a collection of criteria for an MCDM issue, and let $G = (g_1, g_2, ..., g_s)$ be a set of alternatives. The effectiveness or assessment of the alternative $g \in G$ for the criterion h_j is represented by $h_j(g_j)$. The degree to which an option satisfies the mentioned criterion depends on if the goal is to optimize or reduce $h_j(g_j)$. The greater or lesser it is, the better. Consequently, the vector $h(g) = (h_1(g), h_2(g), ..., h_t(g))$ will be used to describe the multifaceted assessment of the alternative $g \in G$. The ELECTRE-III model's assessment processes include threshold function establishment, concordance and discordance index disclosure, credibility degree determination, and option ranking. Let the preference and indifference thresholds be represented, respectively, by b(h) and a(h).

Here, we expand the ELECTRA III method with linguistic neutrosophic fuzzy number. Consider a s alternatives $\{G_1, G_2, ..., G_s\}$, t criteria $\{H_1, H_2, ..., H_t\}$ and α decision maker $\{e_1, e_2, ..., e_\alpha\}$ with weighting vector be $\{w_1, w_2, ..., w_\alpha\}$, then, the procedure of decision-making in the LNFN-ELECTRE III model is described in the following steps:.

Step 1: Determine the concordance matrix

The concordance matrix $C(G_p, G_q)$ is obtained for each pair of alternatives and the CCM is calculated by equation (5).

$$CCM(G_p, G_q) = \frac{\sum_{j=1}^{v} w_j \; CCM_j(G_p, G_q)}{\sum_{j=1}^{v} w_j} \tag{5}$$

where $C_i(p, q)$ is the out ranking degree of the alternative p and the alternative q under the criteria i, and $C_i(p, q)$

$$CCM_i(G_p, G_q) = \begin{cases} 0 \;\; if \quad (G_q) - (G_p) > (a_p) \\ 1 \;\; if \quad (G_q) - (G_p) \leq (b_p) \\ \frac{(a_i)+(G_p)-(G_q)}{(a_p)-(b_p)} \qquad otherwise \end{cases}$$

Step 2: Compute the discordance matrix

Determine the discordance matrix $DCM(G_p, G_q)$. The DCM is described in given equation (6).

$$DCM_i(G_p, G_q) = \begin{cases} 0 \;\; if \quad (G_q) - (G_p) \leq (a_p) \\ 1 \;\; if \quad (G_q) - (G_p) > (b_p) \\ \frac{(G_q)-(G_p)-(a_i)}{(b_p)-(a_p)} \qquad otherwise \end{cases} \tag{6}$$

where, $0 \leq DCM_j(G_p, G_q) \leq 1$.

Step 3: Obtain the outranking degree $O(G_p, G_q)$ is in (7),

$$O(G_p, G_q) = \begin{cases} CCM(G_p, G_q) \qquad if \quad DCM(G_p, G_q) \leq CCM(G_p, G_q) \\ CCM(G_p, G_q) \times \prod_{j \in J} \frac{1-DCM_j(G_p,G_q)}{1-CCM_j(G_p,G_q)} \qquad otherwise \end{cases} \tag{7}$$

Step 4: Lastly, outlining the options according to the values of net credibility, discordance credibility, and concordance credibility.

- The benefit of concordance credibility is explained by,

$$\Psi^{+}(G_i) = \sum_{\forall s \in (i=1,2,\ldots,s)} (G_p, G_q) \tag{8}$$

The outranking character of G_i determines the concordance credibility.

- The following describes the discordance credibility value:

$$\Psi^{-}(G_i) = \sum_{\forall s \in (i=1,2,\ldots,s)} (G_p, G_q) \tag{9}$$

The outranking character of G_i is portrayed by the discordance credibility.

- The description of the net credibility value is provided by,

$$\Psi(G_i) = \Psi^{+}(G_i) - \Psi^{-}(G_i), \quad \forall \;\; G_i \tag{10}$$

A higher worth indicates a significant engaging quality of G_i. The net credibility value represents the worth capability. On the basis of net credibility, both G_is can be fully placed.

5. The fuzzy BWM method

The $(h_1, h_2, ..., h_n)$ are the criterion to select the best decision. The criteria are H_1-technological, H_2-economic, H_3-environmental aspects, and H_4-social.

Step 1: Obtain the greatest criteria (e.g., beneficial criteria) and the lowest criteria (e.g., non-beneficial).

Step 2: Assign scores ranging from 1 to 9 to reflect their preference for the best overall criterion out of all the others. The vector result for Greatest-to-Others is:

$$H_Y = (h_{Y_1}, h_{Y_2}, ..., h_{Y_t})$$

where h_{Y_j} indicates a preference for criterion j (i.e., $h_{YY} = 1$) above the optimal criterion Y. In our example, a vector shows that H_3-environmental features are preferred over the other factors.

Step 3: Sort all of the criteria by preference over the lowest criterion, using a value between 1 and 9. The next-to-lowest vector that is produced is:

$$H_L = (b_{1D}, b_{2D}, ..., b_{sD})$$

where a preference for criterion j over the worst criterion D is indicated by the symbol h_{jD}. The value of $b_{DD} = 1$ is evident. Here, the vector represents the preferences across all criteria over the time-H_2 criteria.

Step 4: Calculate the optimal weights $(w_1^*, w_2^*, ..., w_n^*)$.
The ideal weight for the criteria is one in which $\frac{w_Y}{w_j} = h_{Yj}$ and $\frac{w_j}{w_D} = h_{jD}$ for every pair of $\frac{w_Y}{w_j}$ and $\frac{w_j}{w_D}$. The solution should minimize $|\frac{w_Y}{w_j} - h_{Yj}|$ and $|\frac{w_j}{w_D} - h_{jD}|$ for every j in order to meet these requirements for all j. Take into consideration the weights' non-negativity and sum criteria as follows:

$$\begin{aligned}
&\min \ \max_j \{ |\frac{w_Y}{w_j} - h_{Yj}| - |\frac{w_j}{w_{jD}} - h_{jD}| \} \\
&\text{subject to}
\end{aligned}$$

$$\sum_j w_j = 1, \ \ w_j \geq 1 \ \ \text{forall} \ \ \text{j} \tag{11}$$

Equation (11) can be applied to the subsequent issue:

$$\begin{aligned}
&min \ \ \chi, \\
&subject \ to \\
&\left| \frac{w_Y}{w_j} - h_{Yj} \right| \leq \chi, \ \ \text{forall} \ \ \text{j} \\
&\left| \frac{w_j}{w_D} - h_{jD} \right| \leq \chi, \ \ \text{forall} \ \ \text{j} \\
&\sum_{j=1}^{t} w_j = 1, \forall j \\
&w_j \geq 0, \forall j
\end{aligned} \tag{12}$$

Equation (12) must be solved to determine the ideal weights $(w_1^*, w_2^*, ..., w_n^*)$ and χ^*.Next, we provide a consistency ratio (CR) with χ^*. The greater the CR and the less trustworthy the contrasts become, the larger the χ^*.

Table 2: *Consistency index (CI)*

h_{YD}	1	2	3	4	5	6	7	8	9
CI	0.0	0.71	1.05	1.53	2.07	3.00	3.99	4.79	5.80

5.1. Consistency ratio

In this section, we provide a percentage of consistency for the suggested best-worst technique.

In this case, h_{Yj} indicates the preference of the best criteria over j, and h_{jD} is the preference of the worst criteria j, and h_{YD} indicates the preference of the best criteria over the worst criteria. This makes the comparison totally consistent when $h_{Yj} \times b_{jD} = b_{YD} \ \forall j$.

Furthermore, it is possible for some j to be inconsistent; in this case, we propose a CR to show the consistency of a comparison. In order to achieve this, we start by determining the minimal consistency of a comparison, which is as follows:

As previously stated, where $h_{ij} \in \{1, 2, ..., h_{HD}\}$ the largest possible value of h_{YD} is 9. Consistency decreases when $h_{Yj} \times h_{jD}$ is smaller or larger than h_{YD} or equivalently $h_{Yj} \times h_{jD} \neq 1$, and the largest inequality occurs when h_{Yj} and h_{jD} have the maximum value, which will result in χ. We also know that $(\frac{w_Y}{w_j}) \times (\frac{w_j}{w_D}) = \frac{w_Y}{w_D}$, and given the largest in equality as a results by h_{Yj} and h_{jD}, χ is a value that must be subtracted from h_{Yj} and b_{jD}, then added to b_{YD}, or:

$$(h_{Yj} - \chi) \times (h_{jD} - \chi) = (h_{YD} + \chi) \tag{13}$$

Regarding the minimum degree of consistency $h_{Yj} = h_{jD} = h_{YD}$, we have

$$\begin{aligned} &(h_{YD} - \chi) \times (h_{YD} - \chi) = (h_{YD} + \chi) \\ &\implies \chi^2 - (1 + 2h_{YD})\chi + (b_{YD}^2 - h_{YD}) = 0 \end{aligned} \tag{14}$$

By calculating several values of $h_{YD} \in \{1, 2, ..., 9\}$, we may determine the highest χ that can exist (max χ). As the consistency index in Table 2, these values are utilized.

After that, the CR is computed as follows using χ^* and the appropriate consistency index (CI):

$$\text{CR} = \frac{\chi^*}{\text{CI}} \tag{15}$$

6. Numerical Example

The use of ELECTRE-III based on linguistic neutrosophic fuzzy numbers is discussed in this section. The best energy storage technology will be selected by the proposed method. For this purpose, we choose five alternatives based on four criterion which are give below:

The alternatives of energy storage problem:

G_1-Hydrogen storage

G_2-Electrochemical storage

G_3-Mechanical storage

G_4-Electrical storage

G_5-Thermal storage

The criteria is are:

H_1-Technological

H_2-Economic

H_3-Environmental aspects

H_4-Social.

Table 3: *Vector of pairwise comparisons for the greatest criterion*

Criteria	H_1	H_2	H_3	H_4
H_3	7	3	1	5

Table 4: *Vector of pairwise comparisons for the lowest criterion*

	H_2
H_1	5
H_2	1
H_3	7
H_4	3

6.1. The fuzzy BWM method

Step 1: Construct the criteria list.

Here, we examine the criteria $(H_1, H_2, ..., H_n)$ that is used to make a decision. The criteria are H_1-technological, H_2-economic, H_3-environmental aspects, and H_4-social.

Step 2: Determine which criteria are greatest and lowest. For this particular problem, the greatest and lowest criteria are (H_3)-environmental aspects and H_2-economic.

Step 3: Table 3 provides the pairwise comparison vector for the greatest criterion values.

Step 4: Table 4 provides the pairwise comparison vector for the lowest criterion values.

Step 5: From Table 3 and Table 4 results in equation (8) for this problem, as follows:

$$\begin{aligned}
& min \;\; \chi, \\
& s.t \\
& \left|\frac{w_3}{w_1} - u_{31}\right| \leq \chi, \left|\frac{w_3}{w_2} - u_{32}\right| \leq \chi, \left|\frac{w_3}{w_4} - u_{34}\right| \leq \chi, \;\; \text{forall} \;\;\; \text{j} \\
& \left|\frac{w_1}{w_2} - u_{12}\right| \leq \chi, \left|\frac{w_3}{w_2} - u_{32}\right| \leq \chi, \left|\frac{w_4}{w_2} - b_{42}\right| \leq \chi, \;\; \text{forall} \;\;\; \text{j} \\
& w_1 + w_2 + w_3 + w_4 = 1, \\
& w_1, w_2, w_3, w_4 \geq 0, \forall j
\end{aligned} \tag{16}$$

Solving this equation (38), we get the optimal weights $(w_1^*, w_2^*, ..., w_n^*)$ are $w_1 = 0.0853$, $w_2 = 0.1989$, $w_3 = 0.5965$, $w_4 = 0.1193$ and $\chi^* = 0.1858$. For the consistency ratio, as $b_{GP} = b_{34} = 6$, the CI is 3.01 (Table 3), and the CR is $\frac{0.1858}{3.01} = 0.0617$, it suggests excellent consistency.

6.2. The LNFN-ELECTRE-III method

The linguistic scale for linguistic neutrosophic fuzzy number and initial DM are given in Table 5 and Table 6.

Step 1: Construct the initial matrix

Table 5 and Table 6 shows how the first matrix was constructed using the linguistic scale and how decision-makers assessed energy storage technology based on the expert's matrix's chosen criteria.

Step 2: Obtain the concordance matrix (CCM)

The thresholds for alternatives in the concordance matrix are constructed and provided in Table 7.

Using equation (5) to compare the alternatives, the CCM is now calculated; the results are presented in Table 8.

Step 3: Obtain the discordance matrix

Table 5: *The linguistic scale for LNFN*

l_0	extremely low
l_1	very low
l_2	low
l_3	slightly low
l_4	medium
l_5	slightly high
l_6	high
l_7	very high
l_8	extremely high

Table 6: *The initial decision matrix*

Alternatives	H_1	H_2	H_3	H_4
G_1	$< l_6, l_2, l_4 >$	$< l_8, l_3, l_1 >$	$< l_4, l_2, l_5 >$	$< l_1, l_4, l_3 >$
G_2	$< l_3, l_5, l_7 >$	$< l_6, l_1, l_4 >$	$< l_5, l_1, l_3 >$	$< l_4, l_3, l_3 >$
G_3	$< l_6, l_4, l_8 >$	$< l_4, l_3, l_2 >$	$< l_7, l_1, l_1 >$	$< l_3, l_5, l_7 >$
G_4	$< l_3, l_2, l_5 >$	$< l_2, l_1, l_1 >$	$< l_6, l_3, l_4 >$	$< l_1, l_3, l_6 >$
G_5	$< l_5, l_1, l_3 >$	$< l_6, l_4, l_2 >$	$< l_5, l_3, l_1 >$	$< l_7, l_3, l_2 >$

Table 7: *The initial decision matrix*

Alternatives	H_1	H_2	H_3	H_4
G_1	0.6666	0.8148	0.5555	0.4444
G_2	0.3333	0.7037	0.7037	0.5925
G_3	0.4444	0.6296	0.8518	0.3333
G_4	0.5185	0.6666	0.4444	0.3703
G_5	0.7037	0.6666	0.7037	0.7407
a	0.1	0.1	0.1	0.1
b	0.2	0.2	0.2	0.2
v	0.5	0.5	0.5	0.5

Table 8: *The concordance matrix*

	G_1	G_2	G_3	G_4	G_5
G_1	1	0.321	0.404	1	0.881
G_2	0.915	1	1	1	0.915
G_3	0.915	0.881	1	1	0.795
G_4	0.083	0.284	0.404	1	0.284
G_5	0.811	1	0.434	1	1

The discordance matrix is obtained using (6) and the results are given in Table 9.

Step 4: Next, using equation (7), the comparison between the CCM and DCM is computed,

Table 9: *The discordance matrix*

	G_1	G_2	G_3	G_4	G_5
G_1	1	0	0.191	0	0.038
G_2	0.038	1	0	0	0.048
G_3	0.006	0.024	1	0	0.099
G_4	0	0.127	0.412	1	0.48
G_5	0	0	0	0	1

and Table 10 provides the credibility matrix.

Step 5: According to the equations (8)-(10), the ranking results are calculated and given in

Table 10: *The credibility matrix*

	G_1	G_2	G_3	G_4	G_5
G_1	1	0.321	0.191	'1	0.881
G_2	0.915	1	1	1	0.915
G_3	0.915	0.881	1	1	0.795
G_4	0.083	0.284	0	1	0.284
G_5	0.811	1	0.434	1	1

Table 11.

Step 6: The ranking order using the LNFN-ELECTRE-III method is $G_2 > G_3 > G_5 > G_1 > G_4$.

Table 11: *The final ranking results*

Alternatives	results	Ranks
G_1	2.377	4
G_2	3.744	1
G_3	3.462	2
G_4	0.036	5
G_5	3.245	3

Therefore, the G_2- Electrochemical is the best technology for energy storage problem.

7. Comparison and sensitivity analysis

In this part, we compare this proposed method's effectiveness with other approaches that are currently in use, including VIKOR and ARAS in the instance of an LNFN. Sensitivity analysis was employed as well for this investigation.

Table 12: *Comparison analysis results*

ESTs	ARAS	Rank	VIKOR	Rank	Proposed method	Rank
G_1	0.7479	4	0.7299	4	2.377	4
G_2	0.8693	3	0.1588	2	3.744	1
G_3	1.0000	1	0.3378	3	3.462	2
G_4	0.6591	5	1.0000	5	0.036	5
G_5	0.9581	2	0	1	3.245	3

7.1. Comparative analysis

To illustrate the efficacy and performance of the suggested model, it is compared in this section to various MCDM techniques found in the literature. The ARAS model and the VIKOR model are two methods that have already been used to evaluate suggested methodologies. Certain MCDM approaches make use of the suggested criterion weights. The comparison of ranking-order findings is presented in Table 12. The results generated by the suggested ranking deviate considerably from the current VIKOR and ARAS approaches. Consequently, in comparison to previous MCDM models, the suggested method yields more trustworthy results.

Table 13: *Weights in sensitivity analysis*

ESTs	Case 1	Case 2	Case 3
H_1	0.0853	0.5965	0.1193
H_2	0.1989	0.0853	0.5965
H_3	0.5965	0.1193	0.1989
H_4	0.1193	0.1989	0.0853

Table 14: *Sensitivity analysis results*

ESTs	Case 1	Rank	Case 2	Rank	Case 3	Rank
G_1	2.377	4	3.278	2	3.356	3
G_2	3.744	1	2.203	3	3.641	1
G_3	3.462	2	2.070	4	3.483	2
G_4	0.036	5	2.000	5	1.93	5
G_5	3.245	3	3.805	1	3.245	4

7.2. Sensitivity analysis

This approach compares the outcomes of three situations in its sensitivity analysis. The weight values of the properties can be seen in Table 13. The study's result is Case 1, and the additional results found by applying various attribute weights are Cases 2 and 3. According to sensitivity analysis, changing an attribute's weights affects the ranking order, which is shown in Table 14.

8. Conclusion

Based on energy storage requirements, this paper proposes a strategy for choosing an appropriate energy storage technology. In this work, we create a transformation and fusion method to convey the information in an LNFN, and we treat the choice of energy storage technologies as an MCDM problem. The weights of the experts and criteria are then determined using ELECTRE-III and the best-worst technique, respectively. On the basis of this, an appropriate energy storage technology can be chosen. The presented approach can be modified for future research, allowing for even more research to be conducted using it. Type-2 fuzzy sets (T2FSs), IFSs, and PFSs, for instance, can be employed to model distinct types of decision-making environments. Additionally, the model can be modified to incorporate additional criteria. Numerous other energy-related problems can also be resolved using this strategy of supporting decision-making.

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