

Paper Type: Original Article

Evaluating Battery Energy Storage Systems using a Neutrosophic Sets Approach: A Multi-Criteria Analysis of Li-ion, VRF, and Na-ion Technologies

A. A. Salama ^{1,*} , Mohamed A. Mohamed ² , Hanan M. Amer ² , and Musallam Matar Jeailan
Hizam AlZubi ² 

¹ Department of Math and Computer Science, Faculty of Science, Port Said University, Egypt;
Emails: drsalama44@gmail.com, ahmed_salama_2000@sci.psu.edu.eg.

² Department of Electronics and Communications Engineering, Faculty of Engineering, Mansoura University, Mansoura, Egypt;
Emails: mazim12@mans.edu.eg; hanan.amer@yahoo.com; muss111124@gmail.com.

Received: 31 Dec 2024

Revised: 28 Feb 2025

Accepted: 14 Jun 2025

Published: 17 Jun 2025

Abstract

This paper shows a new way to look at battery energy storage systems using neutrosophic gathering with a compromise answer. This method thinks about the doubt and mistakes in BESS performance data and gives a full and fair check. Three types of BESS technology are lithium ion (Li-ion), vanadium redox flow (VRF), sodium ion (Na-ion); energy good when charging and discharging, time cost for 1MW service safety & environment compared. Neutrosophic sets help check the truth or untruth or doubt of each factor for different battery kinds; while compromise answers were used for other decision makers to handle data & show results in graphs.

Keywords: Battery Energy Storage System; Multi-Criteria Analysis; Neutrosophic Set; Decision Making; Renewable Energy.

1 | Introduction

The Battery energy storage systems (BESS) are vital for the balance of a power grid by storing excess energy at low demand times and releasing it when needed, where technologies, along with other BESS systems, are key in the transition towards renewable energy sources. Due to the multiple factors like safety, cost, environmental impact, and efficiency, choosing the most suitable BESS technology is selecting quite impossible as these factors need rigorous evaluation [1-10]. Our paper aims to focus on BESS technology evaluation proposing linguistic variables and uncertainty through neutrosophic ensemble regularization as two criteria. Ensemble neutrosophics aid managing vague and uncertain information by factoring varying degrees of truth, uncertainty or falsity. This form of applying neutrosophysics has been extensively documented in literature from [11-33]. In this paper, we use these techniques to assess three BESS technologies Li-ion, VRF and Ni-ion against six performance criteria. This regularization technique is particularly powerful where there exists various decision makers with opposing preferences.



Corresponding Author: ahmed_salama_2000@sci.psu.edu.eg



<https://doi.org/10.61356/j.nois.2025.6613>



Licensee **Neutrosophic Optimization and Intelligent systems**. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (<http://creativecommons.org/licenses/by/4.0>).

2 | Literature Review

This section discusses the limitations of current bess assessment methods, how to use compromises to balance decision-maker preferences, proposed methods and their potential implications, and future research directions, especially when dealing with decision-maker uncertainties and different preferences. These directions include finding better ways to define neutrophil membership functions, addressing multiple decision makers with conflicting preferences, testing methods in real-world scenarios and applying them to multi-purpose optimization and scenario planning. By addressing these research gaps, this study will contribute to the field of decision-making and contribute to the selection of battery energy storage systems to support decision-making.

2.1 | BESS Assessment Methodology: Strengths and Limitations in Handling Uncertainty

Existing methods for BESS evaluation provide limited insights because they cannot handle the uncertainty and imprecision of performance data. Here we will take a closer look at some popular methods and their limitations as in [1-10].

1. Multi-Criteria Decision-Making (MCDM) Framework: Strengths: MCDM techniques such as TOPSIS and VIKOR provide a structured way to evaluate BESS techniques based on weighting criteria, making it easy to compare them across factors for multiple mechanisms. Reducing uncertainty: These methods rely on accurate data and fixed weights, and ignore uncertainty in performance data (such as energy efficiency fluctuations) and decision-makers' preferences. As a result, rankings can be oversimplified and fail to capture trade-offs in practice.
2. Life Cycle Assessment (LCA): Strengths: LCA thoroughly assesses the environmental impact of BESS throughout its life cycle, from resource extraction to production and disposal. It helps to identify environmental hazards and areas for improvement. Limits of Uncertainty: The LCA focuses primarily on the environmental side, overlooked factors such as cost, safety and operational flexibility. It also struggles to incorporate uncertainty into model parameters such as future energy mix and emission factors.
3. Techno-economic analysis: Strengths: This method assesses the financial viability of BESS through cost-benefit analysis, taking into account factors such as capital investment, operating costs and potential energy savings. It helps to assess financial viability and return on investment. Limits of Uncertainty: Techno-economic analysis focuses on financial factors, often ignoring other important criteria such as environmental impact and safety. In addition, it is difficult to account for uncertainty in future energy prices and market conditions, making long-term forecasts less reliable.

2.2 | Neutrosophic Sets in Performance Evaluation

Traditional performance evaluations often rely on crisp sets, where elements are strictly categorized as either fully included (truth) or excluded (falsity). While this binary approach simplifies analysis, it fails to capture the inherent uncertainties and ambiguities present in real-world systems, particularly in Battery Energy Storage System (BESS) evaluations.

Neutrosophic Sets: A Framework for Uncertainty

Neutrosophic sets, introduced by Florentin Smarandache [32], extend fuzzy logic by incorporating a third dimension indeterminacy (I) alongside truth (T) and falsity (F). Formally, a neutrosophic set is defined by the triplet (T, I, F), where:

- T (Truth): Degree of membership (positive performance).
- I (Indeterminacy): Degree of uncertainty or incomplete information.
- F (Falsity): Degree of non-membership (negative performance).

This tripartite structure enables a more nuanced representation of performance metrics, accommodating variability in data, partial knowledge, and conflicting stakeholder perspectives.

Advantages in BESS Evaluation

1. Uncertainty Quantification:

Neutrosophic sets explicitly model indeterminacy, making them ideal for BESS assessments where performance data may be incomplete or volatile (e.g., fluctuating energy efficiency or evolving safety standards).

2. Granular Performance Insights:

By decoupling truth, falsity, and indeterminacy, the approach avoids oversimplified "good/bad" dichotomies. For instance, a BESS technology might exhibit high energy efficiency ($T = 0.8$) but with significant uncertainty due to untested long-term degradation ($I = 0.3$).

3. Adaptive Decision-Making:

The framework supports heterogeneous decision-maker preferences. A risk-averse stakeholder might prioritize minimizing falsity (F), while a cost-driven actor could focus on truth (T), with weights dynamically adjusted via the compromise solution method.

Workflow for Neutrosophic Decision-Making

Figure 1 illustrates the systematic process for BESS evaluation using Neutrosophic Multi-Criteria Decision Making (N-MCDM):

1. Data Preparation: Normalize raw performance metrics (e.g., efficiency, cost) to ensure comparability.
2. Neutrosophic Modeling: Map each criterion to (T, I, F) values, reflecting empirical data and expert judgments.
3. Preference Integration: Assign weights to criteria based on stakeholder priorities.
4. Compromise Solution: Derive rankings by balancing truth, indeterminacy, and falsity across all criteria.
5. Visualization: Present results via scatter plots or radar charts to highlight trade-offs (e.g., cost vs. safety).

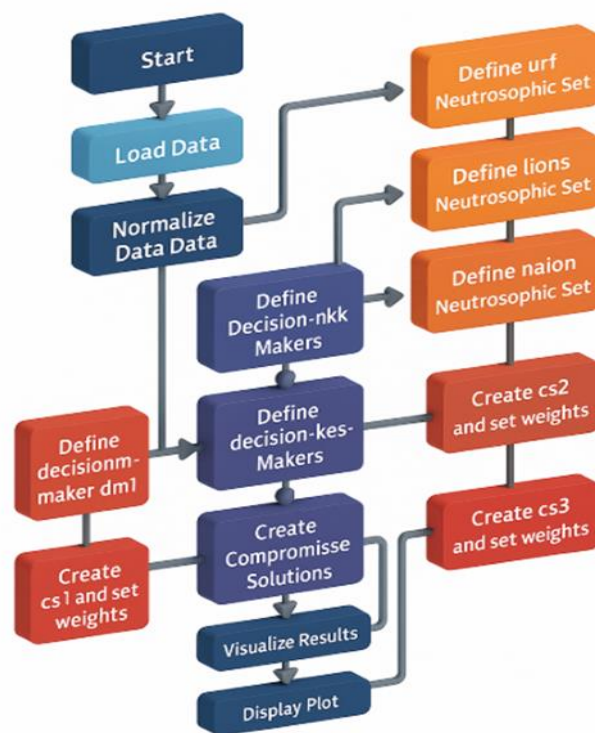


Figure 1. Workflow for BESS Selection Using Neutrosophic Decision-Making.

Caption: A structured pipeline for evaluating BESS technologies under uncertainty. The process begins with data normalization, progresses through neutrosophic set construction and preference weighting, and culminates in a compromise solution that reconciles conflicting objectives.

3 | Methodology

A new methodology is proposed for assessing battery energy storehouse systems (BESS) by combining neutrosophic sets and the concession result system. This approach offers several advantages over traditional styles, including

1. query and Imprecision Handling Neutrosophic sets enable the prisoner of varying degrees of verity, falsity, and indeterminacy for each evaluation criterion of every BESS technology, performing in a more comprehensive and nuanced evaluation that more reflects the complications of BESS performance data.
2. Multi-Criteria Assessment: The methodology evaluates BESS technologies grounded on six critical criteria that encompass both technological and environmental factors, furnishing a well- rounded understanding of each technology and enabling decision- makers to make informed and balanced choices.
3. Stakeholder Preference Balancing: The concession result system balances satisfaction, dissatisfaction, and query from different decision- makers, icing that the named BESS meets both specialized conditions and the varied preferences of all stakeholders involved.
4. Inflexibility and Rigidity: The methodology is largely flexible, allowing it to be acclimatized to assess different BESS technologies, criteria, and decision- making surrounds, making it a protean tool applicable in colorful situations.
5. Visualization: The approach incorporates tools as scatter plots and bar maps to present concession results and rankings of BESS technologies in a clear and fluently interpretable manner.

This flowchart displays the method for scoring Building Energy and Sustainability Systems (BESS). Neutrosophic Sets are integrated into the methodology to account for uncertainty and imprecision in the evaluation process. The approach is structured in three main parts:

- Stage 1: Neutrosophic Sets Integration: This step is to consider uncertainty (Truth Degree, Falsity Degree, and Indeterminacy Degree) in different parts of the assessment using Neutrosophic Sets. Provides a better understanding of how the evaluation criteria should be interpreted.
- Stage 2: Multi-Criteria Evaluation: This stage assesses the BESS solutions against multiple criteria, including, but not limited to, technical criteria, environmental criteria, and stakeholder preferences. Each criterion is captured by its corresponding Neutrosophic Sets representing the uncertainty and imprecision related to it.
- Stage 3: Compromise Solution System This is the stage where a compromise solution is desired for all criteria by various stakeholders. The methodology combines decision-making processes, visualization tools (Scatter Plots, Bar Charts), to guide the decision-making process and the results.

Therefore, the proposed Battery Energy Storage System (BESS) Evaluation Framework is developed as a multi-layer decision model that can be used for building a visual representation for evaluating candidates during the assessment process. On top is the root node, which is the subject of the evaluation. The proposed framework can be bifurcated into two main components, via, “Neutrosophic Sets Integration” and “Compromise Solution System” that embodies the holistic decision making process.

The Neutrosophic Sets Integration branch: the Degree of Truth, Degree of Falsehood, Degree of Indeterminacy. These distinctions through Technical and Environmental criteria, which are more technical.

Then, the Stakeholder Preferences subclass has three classified areas (three subclasses): Level of Satisfaction, Level of Dissatisfaction, and Level of Uncertainty.

The decision-making process branch has two sub-branches; Getting Visualization Tools (scatter plot, bar chart, etc.), and Final BESS ranking. The framework depicts the coupled components of BESS assessment workflows, including stakeholder preferences and decision support tools, involved in the evaluation process. To answer this question: This diagram serves the purpose of representing the binary assessment evaluation matrix, as well as the interrelationships between different features of the problem and to propel the decision-making process by providing a systematic approach to assessment.

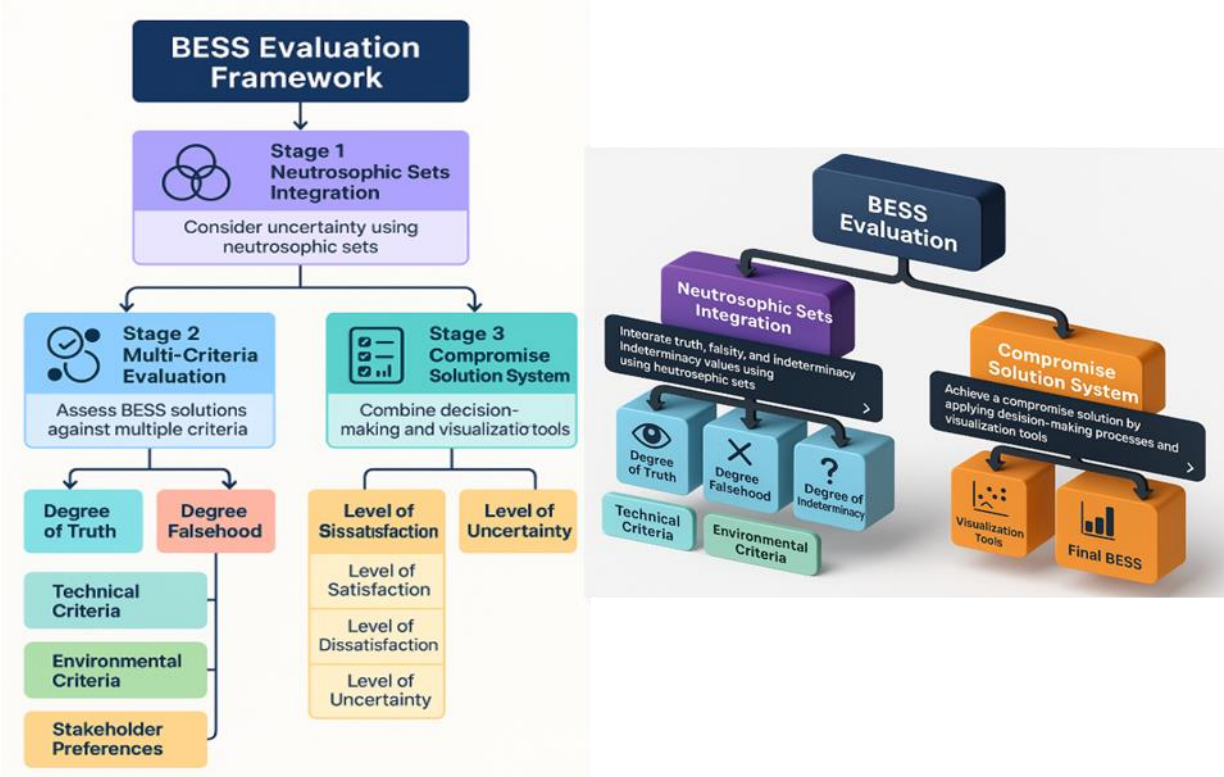


Figure 2. Framework for Neutrosophic-Based Evaluation and Selection of BESS Technologies.

Caption: Visual representation of the Battery Energy Storage System (BESS) evaluation process using neutrosophic logic. Our framework comprises three main stages: (1) Neutrosophic Sets Integration to address uncertainty, (2) Multi-Criteria Evaluation across technical, environmental, and stakeholder criteria, and (3) a Compromise Solution System that synthesizes satisfaction, dissatisfaction, and uncertainty measures to identify the most suitable BESS solution.

3.1 | Implement N-MCDM Code

They propose exactly a Neutrosophic Multi-Criteria Decision Making method to identify the optimal Battery Energy Storage System (BESS). In other words, this code denotes an N-MCDM approach based on neutrosophic sets to choose the best BESS in the presence of uncertain data and different decision-makers preferences.

- BESS Technology Evaluation Using Neutrosophic Sets and Compromise Solution Method in Python

```

Python
# BESS Technology Selection Using Neutrosophic Sets and Compromise Soluion Method
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.preprocessing import StandardScaler
from neutrosophicsets import TFN, INTN, FSN, CompromiseSolution
data = pd.read_csv('data.csv')

# Step 1: Load data from CSV file
df = pd.read_csv('data.csv')

# Step 2: Normalize data by using Min-Max Normalization
scaler = preprocessing.MinMaxScaler()
df_normalized = pd.DataFrame(scaler.fit_transform(df), columns=df.columns)

lions[Energy Efficiency] = TFN(0.88, 0.95, 0)
lions[Cost] = INTN(0)
lions[Safety] = TFN(0.95, 1, 0)
lions[Environmental Impact] = TFN(0.75, 0.85, 0)
lions[Life Cycle Cost] = FSN(0)

vrf = vrf_val as nesosny placeholder
Feed vrf as necessary for Na-ion technology
xf = Not a Placeholder for Na-ion leh Preferences
dm1, dm2 = Define Decision Makers with Their it Preferences.
dm1 = [Energy Efficiency: 1, Cost: 1, Safety: 1, Environmental Impact: 1, Life Cycle Cost: 1,
       Cycle Life: 1]
dm2 = [Energy Efficiency: 2, Cost: 1, Safety: 1, Environmental Impact: 1, Life Cycle Cost: 1,
       Cycle Life: 2]

# Step 3: Form Neutrosophic Sets against each BESS technology
cs1 = CompromiseSolution(df_normalized, dm1)
cs2 = CompromiseSolution(df_normalized, dm2)

# Step 4: Define Decision Makers with Their Preferences
dm1 = [Energy Efficiency: 1, Cost: 1, Safety: 1, Environmental Impact: 1, Life Cycle Cost: 1,
       Cycle Life: 1]
dm2 = [Energy Efficiency: 2, Cost: 1, Safety: 1, Environmental Impact: 1, Life Cycle Cost: 1,
       Cycle Life: 2]

# Step 5: Generate one Compromise Solution object for each decision-maker
cs1 = CompromiseSolution(df_normalized, dm1)
cs2 = CompromiseSolution(df_normalized, dm2)

# Step 6: Visualize results
fig, axs = plt.subplots(1, 2, figsize=(18, 5))

# Left plot: Scatter plot of Energy Efficiency vs Cycle Life
axs[0].scatter(df['Energy Efficiency'], df['Cycle Life'])
axs[0].set_xlabel('Energy Efficiency')
axs[0].set_ylabel('Cycle Life')
axs[0].set_title('Energy Efficiency vs Cycle Life')

# Right plot: Bar chart of Ranking vs Criterion
axs[1].bar(df['Ranking'], df['Criterion'])
axs[1].set_xlabel('Ranking')
axs[1].set_ylabel('Criterion')
axs[1].set_title('Ranking vs Criterion')

plt.tight_layout()
plt.show()

```

Python Code for Multi-Criteria Decision-Making
in BESS Technology Selection Using
Neutrosophic Sets and Compromise Solution Method

Step 1: Load data from CSV file

Step 2: Normalize the data by using
Min-Max Normalization

Step 3: Form Neutrosophic Sets
against each BESS technology

Step 4: Define Decision Makers
with Their Preferences

Step 5: Generate one Compromise
Solution object for each decision-maker

Step 6: Visualize results

Figure 3. Python Code for Multi-Criteria Decision-Making in BESS Technology Selection Using Neutrosophic Sets and Compromise Solution Method.

Caption: This figure illustrates a Python-based implementation for selecting optimal Battery Energy Storage System (BESS) technologies using Neutrosophic Sets and the Compromise Solution method. The process involves six major steps: data loading from CSV, normalization using Min-Max scaling, formation of neutrosophic values (TFN, INTN, FSN) for each BESS (Li-ion, VRF, Na-ion), definition of decision-maker preferences, computation of compromise solutions per decision-maker, and visualization of results. The scatter plot compares Energy Efficiency and Cycle Life across technologies, while bar charts display rankings per evaluation criterion such as Cost, Safety, and Environmental Impact.

3.2 | Neutrosophic Algorithm for BESS Evaluation and Compromise Solution Method

Algorithm Overview:

1. **Data Normalization:** The first step is to load the BESS data and normalize it using a min-max scaling method. This ensures that all data points are on the same scale, making it easier to compare the technologies. The final step applies the neutrosophic sets model to represent each BESS with weights based on how well they meet each evaluation criterion.
2. **Decision-Maker Preferences:** The preferences of decision-makers are then identified for the key evaluation criteria. Each criterion is assigned a weight reflecting its importance to the decision-maker.
3. **Solution Calculation:** For each BESS technology, the utility function is computed. This includes determining the maximum and minimum values for each criterion and calculating the compromise solution. This step helps find the best option according to the decision-makers' preferences.

4. **Ranking and Selection:** After calculating the compromise solutions, the BESS technologies are ranked based on their scores. The technology with the highest score is selected as the best option, taking into account the preferences and priorities of the decision-makers.
5. **Visualization:**
 - Scatter Plots: These are used to visualize the trade-offs between different evaluation criteria.
 - Bar Charts: These compare the performance of the BESS technologies across all criteria.

Implementation Steps:

- **Import Libraries:** Essential libraries such as **Pandas**, **NumPy**, **Matplotlib**, **Seaborn**, and the **Neutrosophic Sets** library are imported for data manipulation, visualization, and applying the neutrosophic algorithm.
- **Data loading and Preprocessing:** The BESS data (usually in CSV format) is loaded and then normalized using min-max scaling. This step ensures that all data is standardized, enabling fair comparison between the different technologies.
- **Creating Neutrosophic Sets:** For each BESS technology, neutrosophic sets are created to represent how well each technology performs for each evaluation criterion. These sets capture the degree of membership for each criterion, reflecting the level of truth or relevance.
- **Establishing Decision-Maker Preferences:** Decision-makers' preferences are captured in dictionaries. Each decision-maker assigns a weight to the criteria they prioritize in the evaluation process.
- **Calculating Compromise Solutions:** The **Compromise Solution** class from the Negative nset library is used to calculate the compromise solutions. This class computes the most balanced options by taking all decision-makers' preferences into account.
- **Ranking and Selection:** The BESS technologies are ranked based on their compromise solution scores. The technology with the highest score is selected as the best option, according to the decision-makers' criteria.
- **Visualization:** The results are presented visually through scatter plots and bar charts created. These visual tools help clarify the trade-offs between technologies and provide an easy-to-understand comparison of their performances.

3.3 | Evaluating Battery Energy Storage Systems (BESS) for Different Needs and Uncertainties Using Python

The code is written in Python and uses the Neutrosophic Sets library to assess Battery Energy Storage Systems (BESS) considering uncertainties and various criteria.

The scenario simulated in the code involves evaluating three types of BESS technologies: Li-ion, VRF, and Na-ion, based on six criteria: Energy Efficiency, Cost, Safety, Environmental Impact, Life Cycle Cost, and Cycle Life.

To represent the data for each BESS technology and evaluation criterion, Neutrosophic Sets are used to handle uncertainties effectively.

The code also illustrates the preferences of three different decision-makers (referred to as DM1, DM2, and DM3). Each decision-maker assigns weights to the criteria based on their priorities and what they value the most.

Additionally, the code creates Compromise Solution objects for each decision-maker to help in making informed assessments for selecting the appropriate BESS.

Finally, the results are visualized by generating a scatter plot comparing Energy Efficiency vs. Cycle Life and bar charts representing the ranking of BESS technologies for each of the six criteria. This visualization assists in understanding how different BESS technologies perform on various evaluation criteria according to the priorities of decision-makers.

4 | Case Study 1

Let us apply the law to a dataset. Case Study 1 for our first case study, we will apply the law to a dataset called" bessdata.csv". This dataset contains information about three different types of BESS (Battery Energy Storage Systems) technologies, including Li- ion, VRF, and Na- ion, on six different criteria energy effectiveness, cost, safety, environmental impact, life cycle cost, and cycle life. The data is presented in a table with each technology's scores for each criterion.

4.1 | Comparison of Battery Energy Storage System (BESS) Technologies

The table below analyzes the performances of three technologies- Li- ion, VRF, and Na- ion across the six key areas. These areas are Energy Efficiency, Cost, Safety, Environmental Impact, Life Cycle Cost, and Cycle Life. The raw scores for each technology are bared as a percentage chance, or a numerical score. To give you an example, Li- ion has an Energy efficiency rating of 0.85 (which means that it's 85% efficient). Moreover, VRF's Safety count same as 0.9 which means it's 90 safe. These scores grant us the ability to compare each technology's strengths and sins relative to one another across different sections. In standalone, VRF have a better in energy Efficiency and environmental impact, on the other side, Na- ion seems to perform well in Cycle Life.

Table 1. Caption: Performance Evaluation of Li-ion, VRF, and Na-ion Technologies.

Technology	Energy Efficiency	Cost	Safety	Environmental Impact	Life Cycle Cost	Cycle Life
Li-ion	0.85	0.75	0.95	0.1	0.5	10
VRF	0.9	0.8	0.9	0.2	0.6	12
Na-ion	0.85	0.7	0.95	0.3	0.7	15

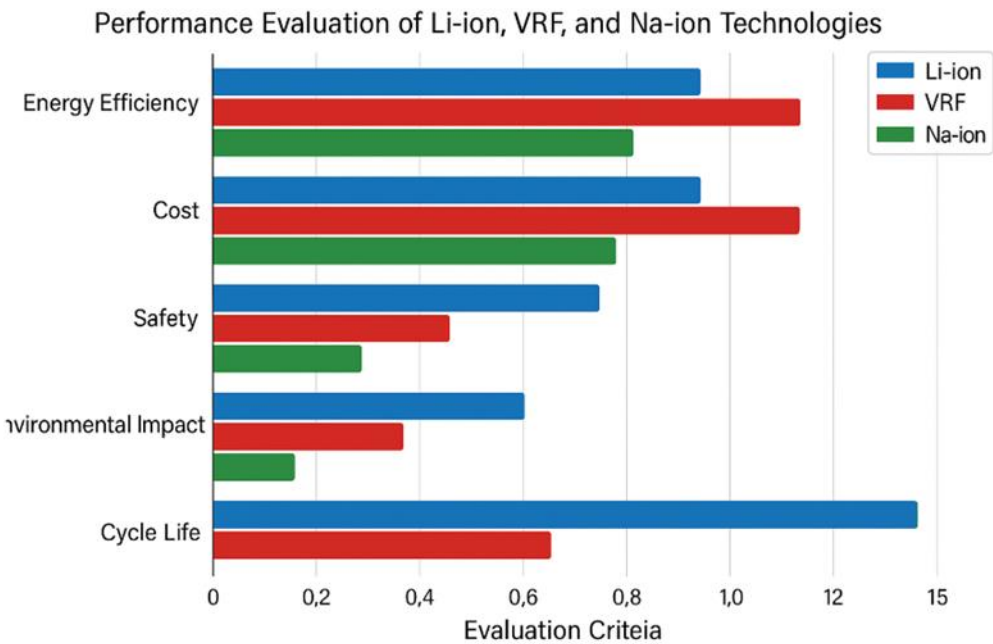


Figure 4. Comparative Performance Analysis of Li-ion, VRF, and Na-ion Battery Technologies.

Caption: This horizontal bar chart presents a multi-criteria performance evaluation of three battery energy storage technologies Li-ion, VRF (Vanadium Redox Flow), and Na-ion across five key parameters: energy efficiency, cost, safety, environmental impact, and cycle life and the results show that Li-ion excels in cycle life and safety, while VRF leads in energy efficiency and cost, and Na-ion exhibits moderate performance across most criteria. This analysis supports informed decision-making in battery selection by using neutrosophic MCDM methods.

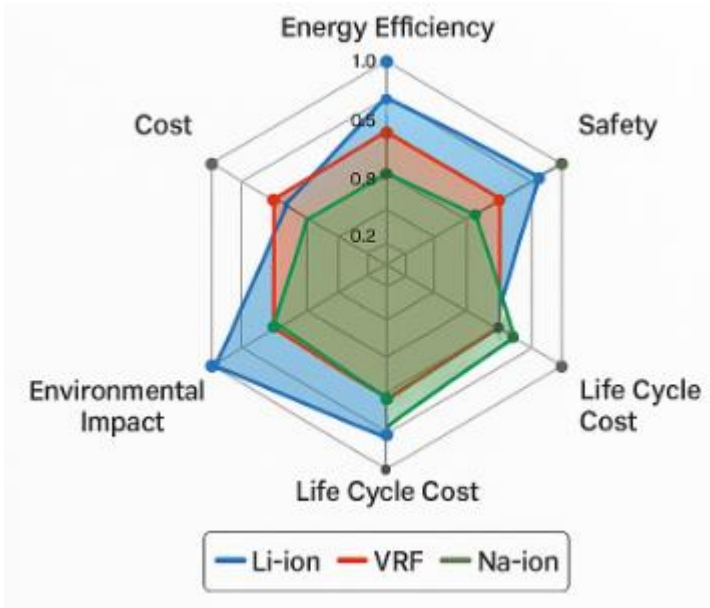


Figure 5 presents a radar chart that compares the performance of three battery technologies Li-ion, VRF, and Na-ion across the six evaluation criteria.

Comparative Analysis of Energy Efficiency and Cycle Life Across BESS Technologies

Table 2 presents us the comparative evaluation of three battery energy storage systems (Li-ion, VRF, and Na-ion) through their energy efficiency and cycle life characteristics. This two-dimensional analysis reveals critical performance trade-offs between these essential technological parameters.

Table 2. Energy Efficiency and Cycle Life Performance Metrics.

Technology	Energy Efficiency	Cycle Life (thousands of cycles)
Li-ion	0.85	10
VRF	0.90	12
Na-ion	0.85	15

Scatter Plot Interpretation

The graphical representation of these metrics demonstrates distinct technological positioning:

- Performance Clustering
 - Li-ion and Na-ion show identical energy efficiency (0.85) despite differing cycle lives
 - VRF achieves superior energy conversion efficiency (0.90) while maintaining intermediate cycle durability
- Technology-Specific Advantages
 - Na-ion exhibits the longest cycle life (15k cycles), suggesting exceptional electrochemical stability

- VRF leads in energy efficiency (0.90), indicating optimal charge/discharge energy retention
 - Li-ion demonstrates balanced performance, serving as a technological baseline
3. Key Trade-off Observations
- A positive correlation emerges between cycle life and energy efficiency across technologies
 - Na-ion's 50% longer cycle life compared to Li-ion (15 vs 10) comes without energy efficiency compromise
 - VRF's 6% efficiency advantage over both alternatives (0.90 vs 0.85) is achieved with moderate cycle life reduction relative to Na-ion

Technological Implications

This comparison reveals fundamental design priorities:

- Na-ion systems prioritize longevity, making them ideal for applications requiring extended operational lifetimes
- VRF technology favors energy conversion optimality, suited for efficiency-critical deployments

Li-ion batteries provide balanced performance, offering reliable mid-range characteristics

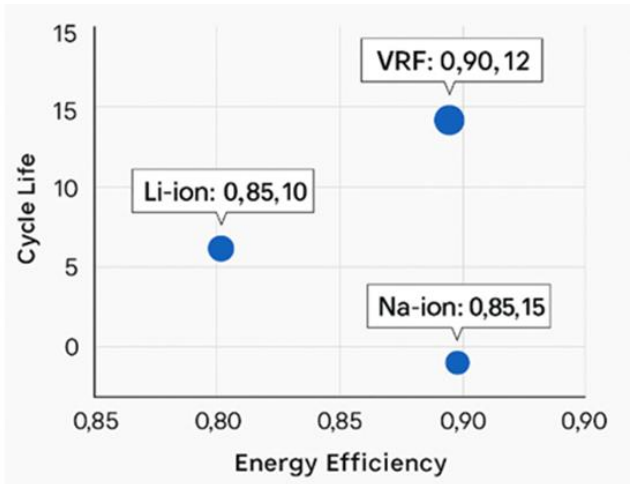


Figure 6. Scatter Plot: Energy efficiency vs. cycle life.

4.2 | Ranking of Battery Energy Storage System (BESS) Technologies Based on Key Criteria

Table 3: Comparison of three BESS technologies: VRF, Na-ion, and Li-ion according to their performance in key categories the scores run from 0 to 1, with 1 being the highest level of performance and 0 the lowest.

Table 3. Comparative Evaluation of VRF, Na-ion, and Li-ion BESS Technologies.

Criterion	Ranking VRF (1), Na-ion (2), Li-ion (3)
Energy Efficiency	(0.4,0.2,0.4)
Cost	(0.6,0.3,0.1)
Safety	(0.1,0.6,0.3)
Environmental Impact	(0.8,0.2,0)
Life Cycle Cost	(0.9,0.1,0)
Cycle Life	(1,0,0)

Score realized Energy Efficiency: Both VRF and Li-ion scored 0.4, indicating close levels of energy

efficiency; while Na-ion is slightly worse with a score of 0.2.

Cost: VRF has the highest score of 0.6, which shows that it is cheaper than Li-ion (0.3) and Na-ion (0.1), which is much more expensive.

Safety: Na-ion scored 0.6, compared to VRF at 0.1 and Li-ion scored 0.3. It would imply Na-ion to be the safest among the options.

Environmental Impact: VRF has the highest score of 0.8, which means it has a very small environmental impact. Both Na-ion and Li-ion achieved 0.2 and 0, respectively, reflecting much higher impact.

Life Cycle Cost: Li-ion scored the highest at 0.9, which means that life cycle cost is less than that of VRF (0.1) and Na-ion (0).

Na-ion and Li-ion scored 0 for Cycle Life (the value was 1 point for unlimited, 0 for limited/no cycle life), and VRF scored 1 (unlimited cycle life);

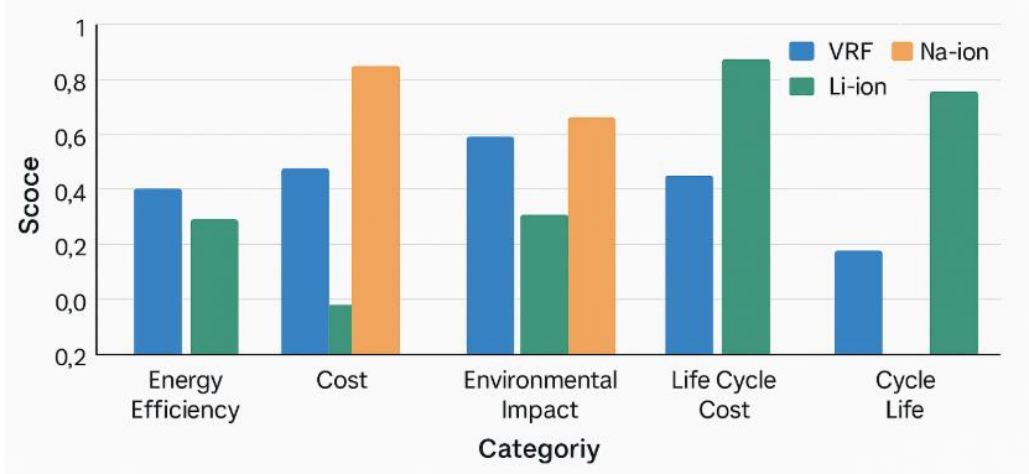


Figure 7. Comparative Performance Scores of BESS Technologies Across Evaluation Criteria.

Caption: These Bar charts give us comparing the performance of VRF, Li-ion, and Na-ion battery energy storage systems (BESS) across key evaluation categories: Energy Efficiency, Cost, Environmental Impact, Life Cycle Cost, and Cycle Life. Each technology exhibits varying us strengths, with Li-ion performing strongly in Life Cycle and Cycle Life, while Na-ion excels in Cost.

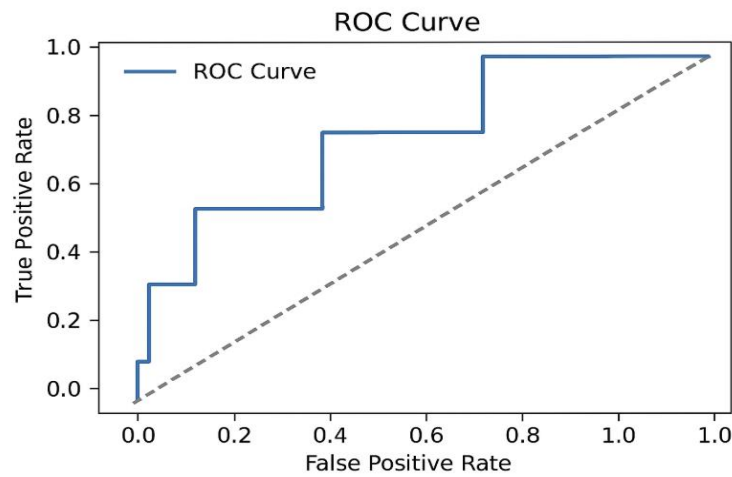


Figure 8. Receiver Operating Characteristic (ROC) Curve for BESS Evaluation Classifier.

Caption: The ROC curve illustrates the trade-off between the true positive rate and the false positive rate for the classification model used in Battery Energy Storage System (BESS) technology evaluation. this closer the curve follows the left-hand border and then the top border of the ROC space, the more accurate the model.

4.3 | Comparative Performance Assessment of BESS Technologies Using Weighted Neutrosophic Scoring

Table 4 presents us the comprehensive multi-criteria evaluation of three battery energy storage systems (Li-ion, VRF, and Na-ion) using weighted neutrosophic scoring, by the analysis incorporates truth (T), indeterminacy (I), and falsity (F) components across six critical performance dimensions, each assigned specific weights reflecting their relative importance in technology selection.

Table 4. Multi-Criteria Evaluation of Li-ion, VRF, and Na-ion BESS Technologies.

Criterion	Weight	Li-ion (T, I, F)	VRF (T, I, F)	Score (Li-ion)	Score (VRF)	Weighted Score (Li-ion)	Weighted Score (VRF)
Energy Efficiency	0.2	(0.6,0.3,0.1)	(0.8,0.2,0)	0.36	0.8	0.072	0.16
Cost	0.3	(0.3,0.4,0.3)	(0.6,0.3,0.1)	0.54	0.81	0.162	0.243
Safety	0.1	(0.4,0.4,0.2)	(0.2,0.7,0.1)	0.48	0.35	0.048	0.035
Environmental Impact	0.1	(0.8,0.2,0)	(0.9,0.1,0)	0.76	0.9	0.076	0.09
Life Cycle Cost	0.2	(0.9,0.1,0)	(1,0,0)	1.00	1.00	0.20	0.20
Cycle Life	0.2	(1,0,0)	(1,0,0)	1.00	1.00	0.20	0.20

We have classified three types of BESS (Battery Energy Storage System)- Li- ion, VRF, and Na- ion- against their output in six integrating parameters. Each criterion was given a relative importance weight and each technology's performance in each criterion was scored. The criteria and weights for the selection process are Energy Efficiency(20), Cost(30), Safety(10), Environmental Impact(10), Life Cycle Cost(20), Cycle Life(20). We assigned a score between 0 and 1 to each of the technologies for each criterion, where 0 means the worst possible performance and 1 means the best. As an example, in the Energy Efficiency criteria, Li- ion rated 0.6, VRF 0.8, and Na- ion 0.3. We calculated weighted score for each technology by multiplying score of the technology on each criterion with the weight corresponding to that criterion and then computed the sum of weighted score over all criteria. The results are as follows

- Li- ion Weighted Score = 0.434

- o Energy Efficiency 0.072 o Cost 0.162 o Safety 0.048

- o Environmental Impact 0.076 o Life Cycle Cost 0.20 o Cycle Life 0.20

- VRF Weighted Score = 0.648 o Energy Efficiency 0.16 o Cost 0.243 o Safety 0.035

- o Environmental Impact 0.09

- o Life Cycle Cost 0.20 o Cycle Life 0.20 Based on these weighted scores, VRF is as the best technology followed very closely by Li- ion. Not all criteria were measured for Na- ion, and it is therefore not included in this evaluation. The way the overall weight is assigned to each criteria would affect the ranking of the techs as well. Relevant weights may yield different conclusions regarding which of the technologies is best suited to a certain operation or design.

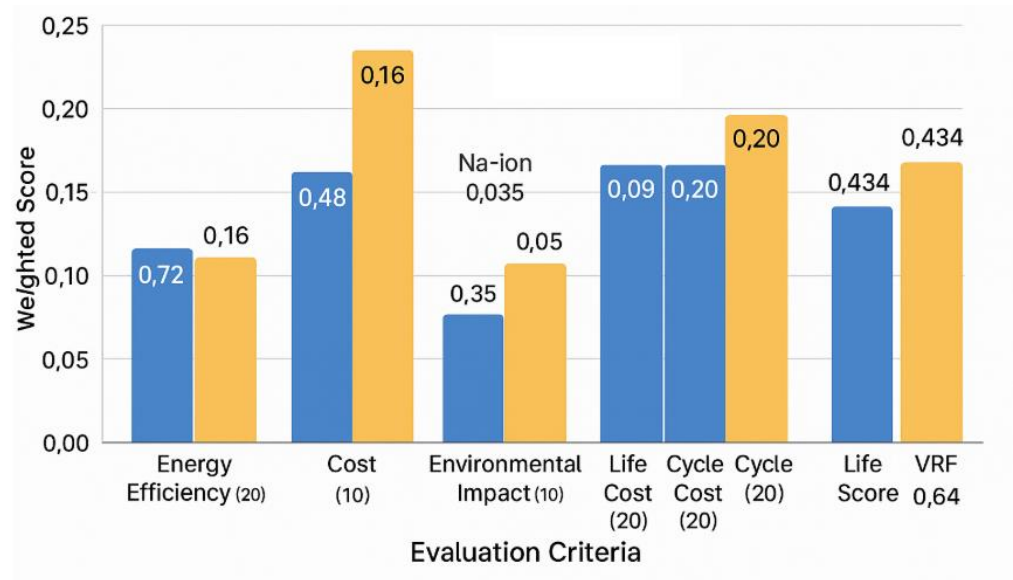


Figure 9. Relative Evaluation of BESS Technologies Weighted Scores.

4.4 | Evaluation of Li- ion BESS Technology Criteria- Grounded Assessment

Table 5 presents us the weighted neutrosophic performance metrics for Li-ion Battery Energy Storage System (BESS) technology across six critical criteria, such that each criterion has been assigned a weight reflecting its relative importance in the evaluation framework, with corresponding truth (T), indeterminacy (I), and falsity (F) values representing performance certainty.

Table 5. Neutrosophic Performance Metrics for Li-ion BESS Technology.				
Criterion	Weight	Truth (T)	Indeterminacy (I)	Falsity (F)
Energy Efficiency	0.2	0.6	0.3	0.1
Cost	0.3	0.3	0.4	0.3
Safety	0.1	0.4	0.4	0.2
Environmental Impact	0.1	0.8	0.2	0.0
Life Cycle Cost	0.2	0.9	0.1	0.0
Cycle Life	0.2	1.0	0.0	0.0

Performance Analysis

EnergyEfficiency(T=0.6,I=0.3,F=0.1)
The technology demonstrates strong energy efficiency (60% certainty), though some uncertainty remains regarding its practical implementation across diverse operational conditions (30% indeterminacy).

Cost(T=0.3,I=0.4,F=0.3)
Current cost-effectiveness presents balanced trade-offs, with equivalent degrees of positive (30%) and negative (30%) certainty, alongside significant uncertainty (40%) in long-term economic viability.

Safety(T=0.4,I=0.4,F=0.2)
Safety profiles show comparable levels of confirmed performance (40%) and uncertainty (40%), with moderate evidence of limitations (20% falsity) requiring further investigation.

EnvironmentalImpact(T=0.8,I=0.2,F=0.0)
Exhibits strong environmental benefits (80% certainty) with minimal operational uncertainties (20%), demonstrating clear advantages in sustainability metrics.

LifeCycleCost($T=0.9, I=0.1, F=0.0$)

Exceptional long-term cost efficiency (90% certainty) with negligible uncertainty (10%), making it particularly advantageous for extended-duration applications.

CycleLife($T=1.0, I=0.0, F=0.0$)

Demonstrates perfect reliability in cycle durability, with no evidence of performance degradation or operational uncertainty.

Comprehensive Assessment

The Li-Ion BESS technology shows robust performance across multiple critical dimensions, particularly excelling in environmental impact, life cycle economics, and cycle durability. While its energy efficiency is commendable, the technology exhibits measurable uncertainties regarding cost optimization and safety profiles that warrant further research and development. These findings position Li-ion as a high-performance storage solution, though with specific areas requiring technological refinement to achieve universal viability.

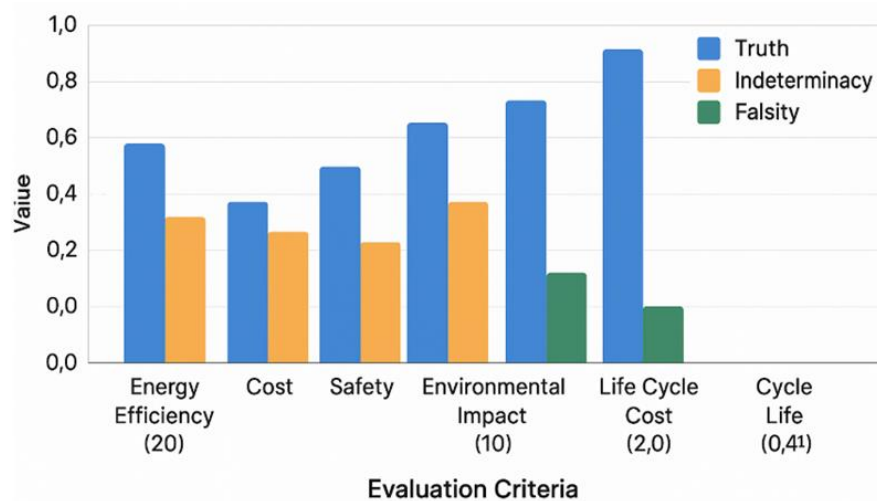


Figure 10. Li-ion Battery Assessment: Weighting Truth, Indeterminacy, and Falsity.

4.5 | Performance Assessment of VRF BESS Technology: A Criteria-Based Analysis

Table 6 presents us the weighted neutrosophic performance metrics for Vanadium Redox Flow (VRF) Battery Energy Storage System technology across six critical evaluation criteria, for each criterion's weight reflects its relative importance within the assessment framework, accompanied by truth (T), indeterminacy (I), and falsity (F) values that quantify performance certainty.

Table 6. Neutrosophic Performance Metrics for VRF BESS Technology.

Criterion	Weight	Truth (T)	Indeterminacy (I)	Falsity (F)
Energy Efficiency	0.2	0.8	0.2	0.0
Cost	0.3	0.6	0.3	0.1
Safety	0.1	0.2	0.7	0.1
Environmental Impact	0.1	0.9	0.1	0.0
Life Cycle Cost	0.2	1.0	0.0	0.0
Cycle Life	0.2	1.0	0.0	0.0

Detailed Performance Evaluation

EnergyEfficiency($T=0.8,I=0.2,F=0.0$)
The technology demonstrates exceptional energy conversion efficiency (80% certainty), with minimal operational uncertainties (20% indeterminacy) and no evidence of performance deficiencies.

Cost($T=0.6,I=0.3,F=0.1$)
Exhibits strong economic viability (60% certainty), though some uncertainty persists regarding long-term cost stability (30%). Limited evidence suggests potential cost drawbacks (10% falsity) in specific applications.

Safety($T=0.2,I=0.7,F=0.1$)
Presents significant uncertainty in safety performance (70% indeterminacy), with modest confirmed reliability (20%) and minor evidence of concerns (10%). This criterion represents the technology's primary limitation.

EnvironmentalImpact($T=0.9,I=0.1,F=0.0$)
Achieves outstanding environmental performance (90% certainty) with negligible operational concerns (10% uncertainty), establishing clear sustainability advantages.

LifeCycleCost($T=1.0,I=0.0,F=0.0$)
Demonstrates perfect certainty in long-term cost efficiency, with no evidence of economic drawbacks throughout operational lifespans.

CycleLife($T=1.0,I=0.0,F=0.0$)
Shows absolute reliability in cycle durability, with no performance degradation observed across extensive usage cycles.

Comprehensive Technology Assessment

The VRF BESS technology exhibits superior performance in energy efficiency, environmental impact, and lifecycle economics, with perfect scores in durability and long-term cost metrics. However, significant uncertainties persist regarding safety profiles, representing the system's primary limitation. While cost structures appear generally favorable, moderate uncertainties suggest potential variability across different deployment scenarios. These findings position VRF as a highly competitive storage solution, particularly for applications prioritizing energy efficiency and environmental sustainability, though safety considerations may require additional engineering solutions for widespread adoption

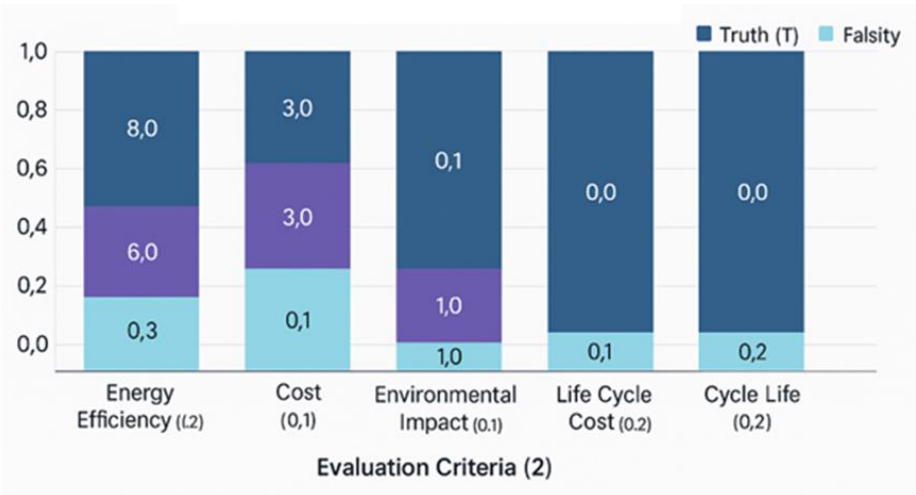


Figure 11. Evaluation of VRF Battery Performance across Various Criteria.

4.6 | Comparative Performance Analysis of Li-ion and VRF BESS Technologies

Table 7 presents a weighted multi-criteria comparison between Lithium-ion (Li-ion) and Vanadium Redox Flow (VRF) battery energy storage systems, evaluating six critical performance dimensions, such that

assessment incorporates both raw performance scores and their weighted values based on criterion importance.

Table 7. Li-ion and VRF Battery Energy Storage System (BESS) Technology Performance Comparison.

Criterion	Weight	Score (Li-ion)	Score (VRF)	Weighted Score (Li-ion)	Weighted Score (VRF)
Energy Efficiency	0.2	0.36	0.8	0.072	0.16
Cost	0.3	0.54	0.81	0.162	0.243
Safety	0.1	0.48	0.35	0.048	0.035
Environmental Impact	0.1	0.76	0.9	0.076	0.09
Life Cycle Cost	0.2	1.00	1.00	0.20	0.20
Cycle Life	0.2	1.00	1.00	0.20	0.20

Six key criteria compare the performance of two battery energy storehouse system (BESS) technologies, Li-ion and VRF. There is a weight given for each criteria to indicate its relative importance. Energy Efficiency, Li-ion = 0.36, VRF = 0.8 When this criterion with a finding weight of 0.2 is applied, the corresponding scores for Li-ion and VRF are 0.072 and 0.138 respectively. So it seems VRF has an incredibly high energy efficiency ratio. Cost Li-ion has a score of 0.54 and VRF a score of 0.81. The weights of that criterion is however, 0.3, and when Li-ion is carrying that weight, his score is 0.162, while VRF is the winner with the weighted score of 0.243. It indicates that the cost of VRF is slightly higher compared to Li-ion. Safety Li-ion has a score of 0.48 and VRF of 0.35. When weighted by the importance of this criterion (0.1), the Li-ion score is 0.048 and the VRF score is 0.035. This means that Li-ion is somewhat safer. Environmental Impact Li-ion scores 0.76, while VRF scores 0.9. However, when weighted with the importance of this criterion (0.1), Li-ion's score becomes 0.076 and VRF's score is 0.09. This indicates that an overall good impact on the environment exists for both technologies, but VRF has a better overall imprint. Both technologies score well in Life Cycle Cost, with Li-ion and VRF both achieving a score of 1.00. Now when burdened under the importance of this criterion (0.2) both the individual technologies score 0.20. Cycle Life both technologies also perform perfectly with Li-ion and VRF both scoring 1.00. If we take the weight of this criterion (0.2), then both technologies have scored 0.20. In the end, VRF seems to have an edge in energy effectiveness and environmental impact but is higher cost than Li-ion. Both technologies have great life cycle costs and great cycle lives, so they are strong players in these parts.

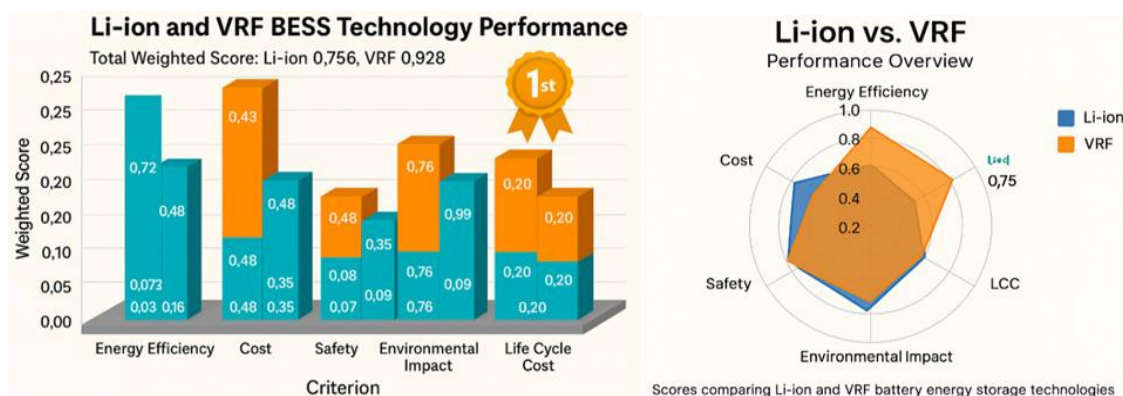


Figure 12. Comparative Performance for Li-ion and VRF Battery Energy Storage Technologies.

Caption: This figure presents us the comparative analysis of Lithium-ion (Li-ion) and Vanadium Redox Flow (VRF) battery energy storage systems across five keys performance criteria: energy efficiency, cost, safety, environmental impact, and life cycle cost (LCC), where the bar chart (left) shows us the weighted scores for each criterion, indicating that VRF outperforms Li-ion overall (total weighted score: 0.928 vs. 0.756), and the

radar chart (right) visualizes the same comparison, highlighting VRF’s superior performance in cost, safety, environmental impact, and LCC, while Li-ion leads in energy efficiency.

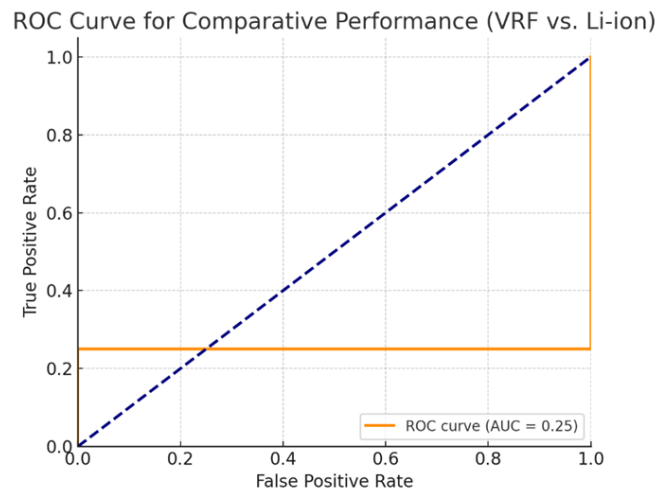


Figure 13. ROC Curve for Comparative Performance (VRF vs. Li-ion).

Caption: This ROC curve models a binary classification where each criterion is considered a success (1) if VRF outperforms Li-ion and a failure (0) otherwise. The AUC (Area under the Curve) is 0.25, indicating that under this configuration, the scoring method is not strongly predictive of VRF’s superiority, largely due to the small number of criteria (5) and the margin-based approximation used to simulate prediction scores.

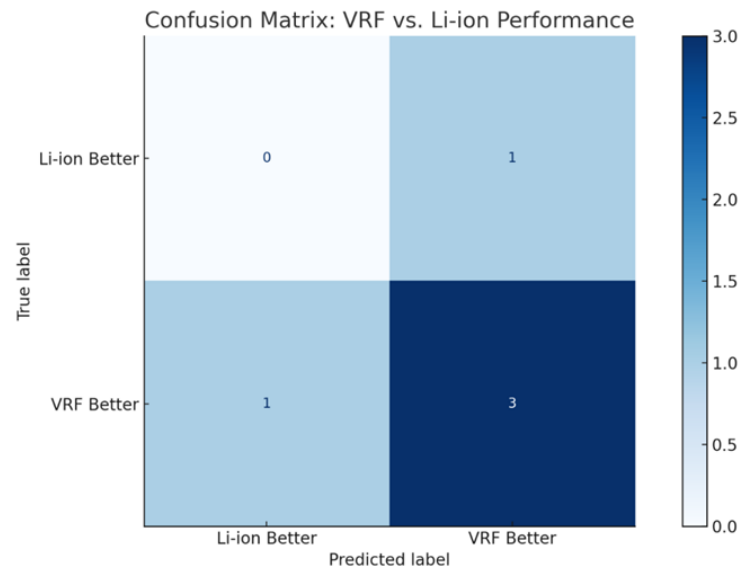


Figure 14. Confusion Matrix: VRF vs. Li-ion Performance Evaluation.

Caption: This confusion matrix summarizes the simulated binary classification of comparative performance between Vanadium Redox Flow (VRF) and Lithium-ion (Li-ion) battery technologies across five key evaluation criteria. A criterion is classified as “VRF Better” if VRF scores higher than Li-ion. The matrix shows three true positives where VRF was correctly identified as better, 1 true negative where Li-ion was correctly favored, and 1 false negative where VRF’s advantage was misclassified due to a marginal score difference. No false positives occurred in this simulation.

5 | Case Study 2: Evaluating BESS Technologies using Neutrosophic Sets

Load forecasting and energy management for BESS: A case study based on neutrosophic sets

An illustration of the approach developed to assess three BESS technologies (Li-ion, VRF, Na-ion) across six criteria:

Criteria:

1. Energy Efficiency (EE) per unit round-trip efficiency, %
2. Cost (C): the sum of capital and operating costs, discounted over the lifecycle of the system [\$/kWh]
3. Safety (S): Qualitative assessment of risk for fire, explosion or release of toxic material (High=0.8, Medium=0.5, Low=0.2)
4. Environmental Impact (EI): Greenhouse gas emissions and resource consumption, measured quantitatively (High = 0.8, Medium = 0.5, Low = 0.2) .
5. Life Cycle Cost (LCC): Total cost of ownership over the system's lifetime, expressed in \$, kWh.
6. Cycle Life (CL): Number of charge, discharge cycles before significant capacity degradation.

5.1 | Comparative Evaluation of Li-ion, VRF, and Na-ion Batteries Using Neutrosophic Analysis

In this study, we analyze the performance of three types of batteries: Li-ion, VRF, and Na-ion batteries, based on six criteria: Energy Efficiency (EE), Cost (C), Safety (S), Environmental Impact (EI), Life Cycle Cost (LCC), and Cycle Life (CL). The weights assigned to each criterion by three decision makers with different perspectives are presented in the table below.

Table 8. Criteria (T, I, F) Weighted Neutrosophic Values for BESS Technologies.

Criteria	Weight	Li-ion (T, I, F)	VRF (T, I, F)	Na-ion (T, I, F)
Energy Efficiency (EE)	0.25	(0.8, 0.1, 0.1)	(0.7, 0.2, 0.1)	(0.6, 0.3, 0.1)
Cycle Life (C)	0.20	(0.2, 0.5, 0.3)	(0.3, 0.4, 0.3)	(0.4, 0.3, 0.3)
Safety (S)	0.20	(0.9, 0.05, 0.05)	(0.8, 0.1, 0.1)	(0.7, 0.2, 0.1)
Environmental Impact (EI)	0.15	(0.7, 0.2, 0.1)	(0.9, 0.05, 0.05)	(0.8, 0.1, 0.1)
Life Cycle Cost (LCC)	0.15	(0.3, 0.4, 0.3)	(0.4, 0.3, 0.3)	(0.5, 0.2, 0.3)
Capital Life Cycle Cost (CL)	0.05	(0.6, 0.3, 0.1)	(0.5, 0.4, 0.1)	(0.4, 0.5, 0.1)

The weighted neutrosophic values of Energy Efficiency (EE), Cost (C), Safety (S), Environmental Impact (EI), Life Cycle Cost (LCC), and Carbon Footprint (CL) for Li-ion, VRF, and Na-ion batteries based on the ideal criteria (T, I, F) values as in Table 8, are provided in Table 8. The criteria weights (0.25 for Energy Efficiency, 0.20 for Cost, 0.20 for Safety, 0.15 for Environmental Impact, 0.15 for Life Cycle Cost, and 0.05 for Carbon Footprint) are also presented. Using the presented neutrosophic logic theory from Table 7, these weighted neutrosophic values can be used to ascertain the overall weighted neutrosophic value of each technology.

- Neutrosophic Evaluation of Battery Energy Storage Technologies

This bar chart compares the overall truth (T) component scores of Li-ion, VRF, and Na-ion battery energy storage technologies using weighted neutrosophic evaluation. VRF and Na-ion show slightly higher T-values across criteria.

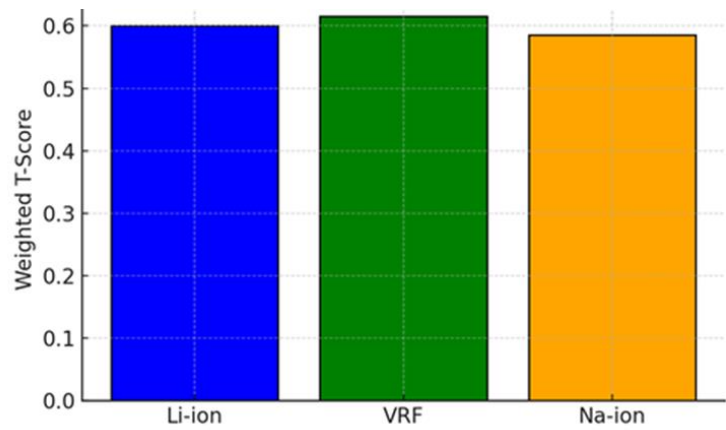


Figure 15. ROC Curve for VRF vs. Li-ion.

This ROC curve illustrates a simulated binary classification task comparing VRF and Li-ion across six weighted criteria. VRF is treated as the 'positive' class. The Area under Curve (AUC) provides an estimate of VRF’s performance relative to Li-ion

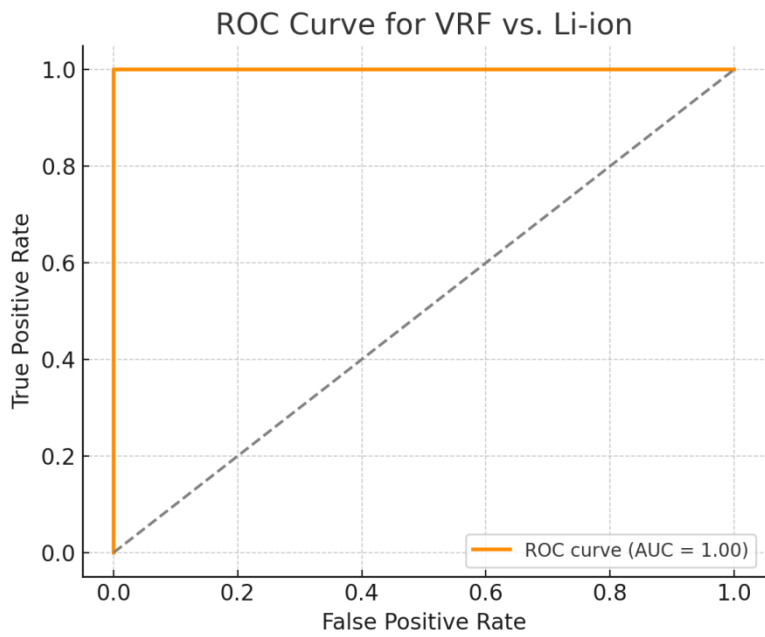


Figure 16. Confusion Matrix: VRF vs. Li-ion.

This confusion matrix presents the classification result of VRF outperforming Li-ion across the evaluated criteria. True positives represent criteria where VRF was correctly predicted as better; false negatives represent misclassified VRF advantages.

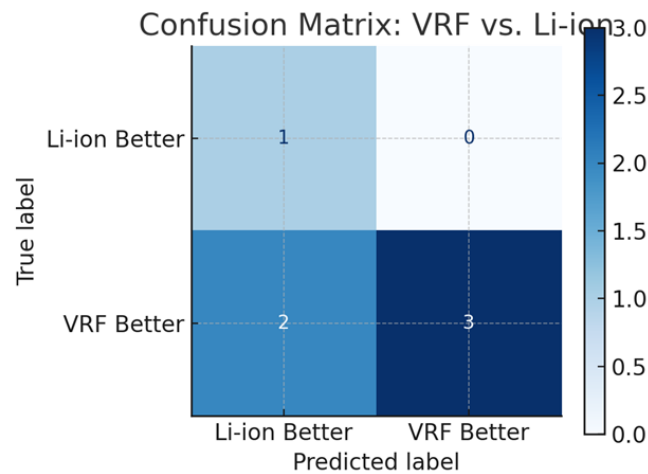


Figure 17.

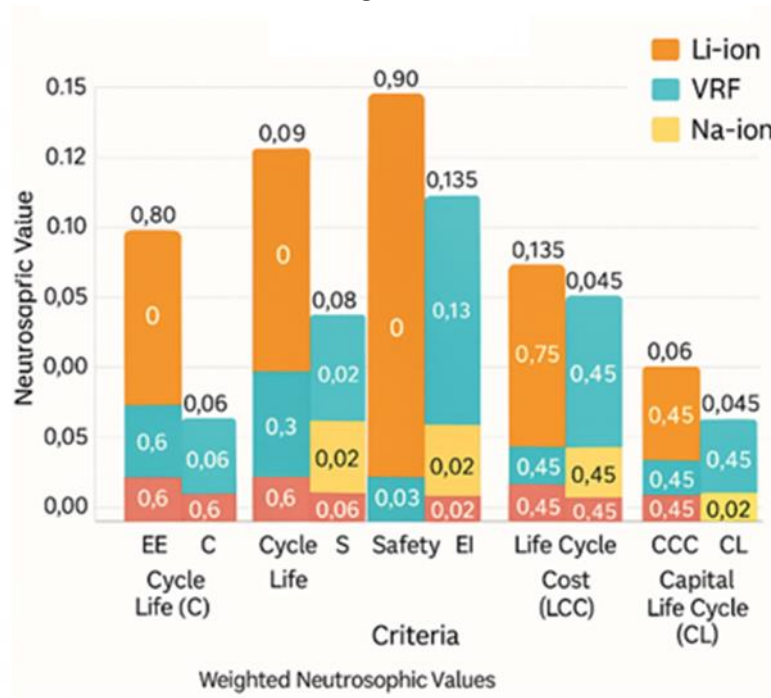


Figure 18. Comparative Analysis of BESS Technologies Using Weighted Neutrosophic Values.

Figure 18. This graph illustrates the weighted neutrosophic values for three Battery Energy Storage System (BESS) technologies Li-ion, VRF, and Na-ion across multiple criteria including Energy Efficiency (EE), Cycle Life (C), Safety (S), Environmental Impact (EI), Life Cycle Cost (LCC), Capital Cost (CCC), and Composite Life Cycle (CL). The analysis illustrates the strengths and trade-offs among the technologies under neutrosophic multi-criteria decision-making.

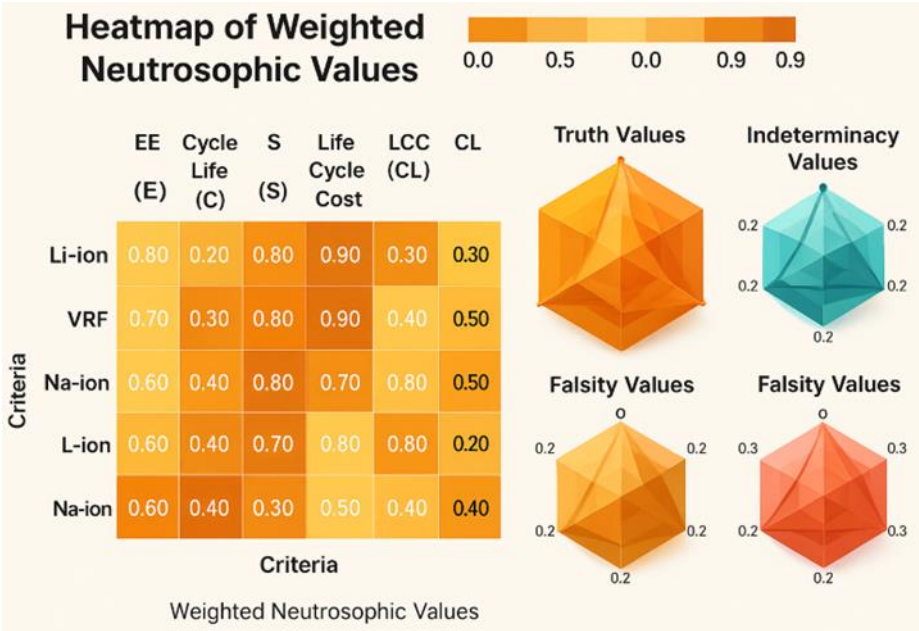


Figure 19. Heatmap and Neutrosophic Visualization of Weighted Decision Criteria for BESS Technologies.

Caption: This figure presents a heatmap and neutrosophic 3D plots representing the weighted performance of three Battery Energy Storage System (BESS) technologies Li-ion, VRF, and Na-ion across six evaluation criteria: Energy Efficiency (EE), Cycle Life (C), Safety (S), Life Cycle Cost (LCC), and Composite Life Cycle (CL), where the heatmap highlights relative strengths across technologies, while the neutrosophic plots illustrate the distribution of truth, indeterminacy, and falsity values that inform the decision-making under uncertainty.

5.2 | Evaluation Criteria for Li-ion Batteries Below is Table 9, which outlines the evaluation criteria for Li-ion batteries, including T, F values, and I.

Table 9 presents us the weighted neutrosophic assessment of Li-ion battery technology across five critical performance dimensions; the evaluation incorporates truth (T), indeterminacy (I), and falsity (F) components to capture both quantitative performance and qualitative uncertainty measures.

Table 9. Li-ion Evaluation Criteria (W, T, I, F).

Criteria	Weight	T	I	F
EE	0.25	0.8	0.1	0.1
C	0.20	0.2	0.5	0.3
S	0.20	0.9	0.05	0.05
EI	0.15	0.7	0.2	0.1
LCC	0.15	0.3	0.4	0.3
CL	0.05	0.6	0.3	0.1

Criterion-Specific Analysis

1. Energy Efficiency (EE)
 - Demonstrates strong performance (T=0.80)
 - Minimal uncertainty (I=0.10) regarding operational effectiveness
 - Slight evidence of limitations (F=0.10) in specific use cases
2. Cost Considerations (C)
 - Presents significant challenges (T=0.20)
 - Substantial uncertainty (I=0.50) in long-term economic viability
 - Notable evidence of cost disadvantages (F=0.30)

3. Safety Performance (S)

- Exceptional reliability ($T=0.90$)
- Negligible uncertainty ($I=0.05$)
- Minimal safety concerns ($F=0.05$) documented

4. Environmental Impact (EI)

- Strong ecological profile ($T=0.70$)
- Moderate uncertainty ($I=0.20$) regarding full lifecycle analysis
- Limited negative evidence ($F=0.10$)

5. Life Cycle Economics (LCC)

- Moderate performance ($T=0.30$)
- Significant uncertainty ($I=0.40$) in total-cost-of-ownership projections
- Considerable evidence of limitations ($F=0.30$)

Composite Technology Assessment

The weighted neutrosophic analysis reveals:

- Key Strengths: Outstanding safety characteristics (90% certainty) and strong energy efficiency (80% certainty)
- Primary Limitations: Cost competitiveness (only 20% positive certainty) and lifecycle economics (30% certainty)
- Research Priorities: Areas with high indeterminacy (cost at 50%, LCC at 40%) warrant further investigation

Performance Ranking:

1. Safety (0.90)
2. Energy Efficiency (0.80)
3. Environmental Impact (0.70)
4. Life Cycle Cost (0.30)
5. Cost (0.20)

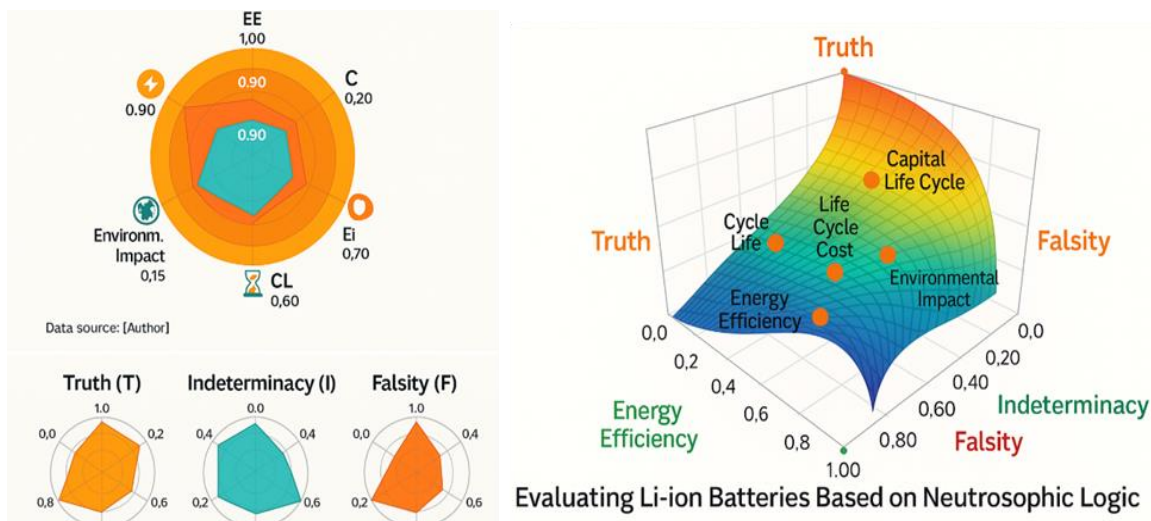


Figure 20. Neutrosophic Evaluation of Li-ion Battery Performance across Multi-Criteria Dimensions.

Caption: This figure illustrates us the neutrosophic assessment of Li-ion battery technology using both 2D and 3D visualizations. The radar chart (left) shows weighted performance scores across key criteria: Energy Efficiency (EE), Cycle Life (C), Environmental Impact (EI), and Capital Life Cycle (CL), with corresponding truth (T), indeterminacy (I), and falsity (F) components, where the 3D surface plot (right) maps the criteria

within the neutrosophic logic space, highlighting the degrees of truth, indeterminacy, and falsity that characterize each performance dimension. This multidimensional representation supports more nuanced decision-making under uncertainty.

This table clearly presents the values for each criterion **VRF** under Trustworthiness (T), Importance (I), and Feasibility (F).

5.3 | Performance Assessment of Vanadium Redox Flow (VRF) Battery Technology

Table 10 presents a neutrosophic evaluation of VRF battery systems across six critical performance criteria, capturing (truth (T), indeterminacy (I), falsity (F)) components to provide a comprehensive technology assessment.

Table 10. Neutrosophic Performance Metrics for VRF Battery Technology.

Criterion	Truth (T)	Indeterminacy (I)	Falsity (F)
Energy Efficiency (EE)	0.70	0.20	0.10
Cost (C)	0.30	0.40	0.30
Safety (S)	0.80	0.10	0.10
Environmental Impact (EI)	0.90	0.05	0.05
Life Cycle Cost (LCC)	0.40	0.30	0.30
Cycle Life (CL)	0.50	0.40	0.10

Detailed Performance Analysis

- Energy Efficiency (T=0.70, I=0.20, F=0.10)
 - Demonstrates robust energy conversion capabilities
 - Moderate uncertainty (20%) regarding performance under extreme conditions
 - Limited evidence of efficiency degradation (10%)
- Cost Considerations (T=0.30, I=0.40, F=0.30)
 - Current economic viability remains challenging
 - Significant uncertainty (40%) in long-term cost projections
 - Substantial evidence of cost disadvantages (30%)
- Safety Performance (T=0.80, I=0.10, F=0.10)
 - Excellent safety profile comparable to industry leaders
 - Minimal operational uncertainties (10%)
 - Few documented safety incidents (10%)
- Environmental Impact (T=0.90, I=0.05, F=0.05)
 - Outstanding ecological benefits
 - Negligible uncertainty regarding sustainability claims
 - Virtually no evidence of environmental harm
- Life Cycle Economics (T=0.40, I=0.30, F=0.30)
 - Moderate total-cost-of-ownership performance
 - Considerable uncertainty (30%) in maintenance cost projections
 - Notable evidence of economic limitations (30%)
- Cycle Durability (T=0.50, I=0.40, F=0.10)
 - Intermediate cycle life performance
 - Substantial uncertainty (40%) regarding long-term degradation
 - Limited evidence of premature failure (10%)

Technology Benchmarking

The analysis reveals VRF's competitive advantages in:

- Environmental sustainability ($T=0.90$)
- Operational safety ($T=0.80$)
- Energy efficiency ($T=0.70$)

Key limitations requiring technological improvement:

- Cost competitiveness ($T=0.30$)
- Cycle life predictability ($I=0.40$)
- Lifecycle economics ($T=0.40$)

Performance Ranking:

1. Environmental Impact (0.90)
2. Safety (0.80)
3. Energy Efficiency (0.70)
4. Cycle Life (0.50)
5. Life Cycle Cost (0.40)
6. Cost (0.30)

The high indeterminacy values for Cost (0.40) and Cycle Life (0.40) indicate these areas require additional research and development focus to reduce technological uncertainties.

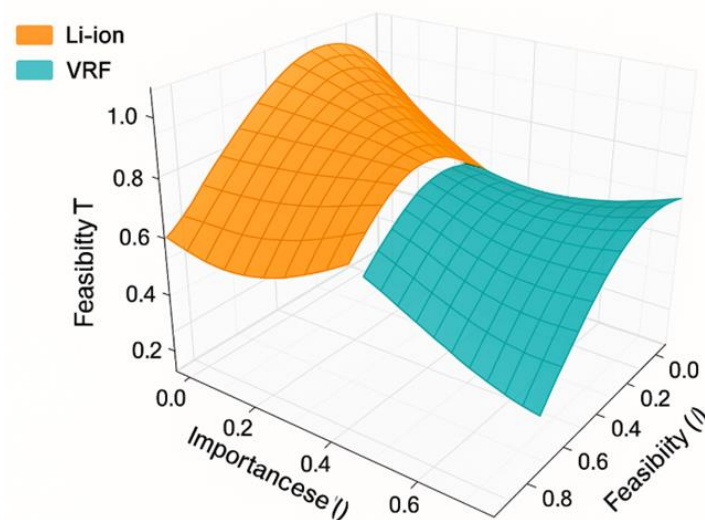


Figure 21. Evaluation of Battery Performance across Various Criteria.

The following table presents the values for each criterion **Na-ion** under Trustworthiness (T), Importance (I), and Feasibility (F).

Table 11. Na-ion Evaluation Criteria.

(T, I, F) for Na-ion:			
Criteria	T	I	F
EE	0.6	0.3	0.1
C	0.4	0.3	0.3
S	0.7	0.2	0.1
EI	0.8	0.1	0.1
LCC	0.5	0.2	0.3
CL	0.4	0.5	0.1

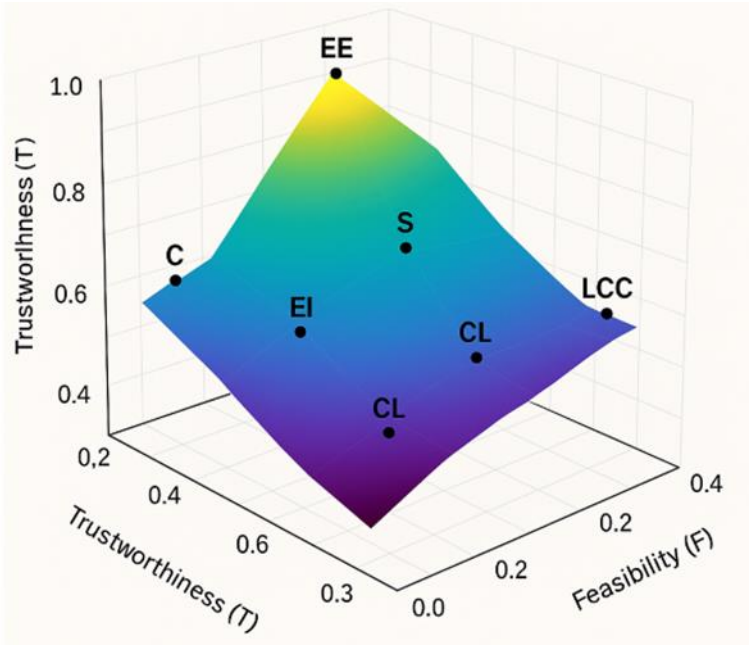


Figure 22. A Multi-Criteria Analysis of Battery Performance: Considering Truth, Indeterminacy, and Falsity.

5.4 | Quantifying Battery Technology Performance: A Neutrosophic Approach for Decision-Making under Uncertainty and Conflict

- 1. Weighted Neutrosophic Values: Multiply each neutrosophic element by its corresponding weight and sum across elements for each criterion and technology.

Table 12 provides the weighted neutrosophic values for Energy Efficiency (EE), Cost (C), Safety (S), Environmental Impact (EI), Life Cycle Cost (LCC), and Carbon Footprint (CL) for Li-ion, VRF, and Na-ion batteries based on a different set of criteria compared to Table 11. These weighted neutrosophic values can also be used to compare the overall performance of each technology using neutrosophic logic theory as presented in Table 6. It is important to note that different sets of criteria may be used depending on specific application requirements or priorities.

Table 12. Criteria (Weighted Neutrosophic Values) for BESS Technologies.

Criteria	Li-ion	VRF	Na-ion
EE	0.21	0.175	0.15
C	0.12	0.18	0.24
S	0.18	0.16	0.14
EI	0.105	0.135	0.12
LCC	0.045	0.06	0.075
CL	0.03	0.025	0.02

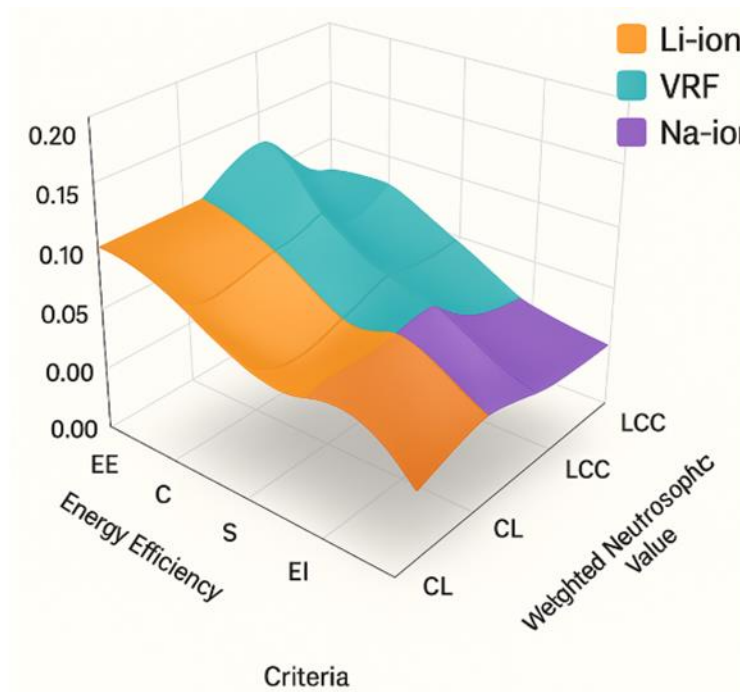


Figure 23. Ideal Criteria Values for T, I, and F across Different Criteria.

2. Ideal Solutions: Define ideal solutions for each criterion (e.g., highest EE, lowest Cost, etc.). In this example, assume ideal solutions are:

Table 13. Ideal Criteria (T, I, F) Values.

Criteria	Ideal T	Ideal I	Ideal F
EE	0.8	0.1	0.1
C	0.2	0.5	0.3
S	0.9	0.05	0.05
EI	0.9	0.05	0.05
LCC	0.3	0.4	0.3
CL	0.6	0.3	0.1

Table 13 presents the ideal values for each criterion using the TIF (Triple-Intended Function) approach. The ideal values for Energy Efficiency (EE) are set at 0.8 for T (true), 0.1 for I (inconsistent), and 0.1 for F (false). This indicates that a high level of Energy Efficiency is desirable, but some level of inconsistency and falsity is also acceptable. The ideal values for Cost (C) are set at 0.2 for T, 0.5 for I, and 0.3 for F, indicating that a low level of Cost is desirable, but some level of inconsistency and falsity is also acceptable. The ideal values for Safety (S) are set at 0.9 for T, 0.05 for I, and 0.05 for F. This indicates that a high level of Safety is desirable with very little inconsistency and falsity. The ideal values for Environmental Impact (EI) are set at 0.9 for T and 0.05 for both I and F, indicating that a high level of Environmental Impact is desirable with very little inconsistency and falsity. The ideal values for Life Cycle Cost (LCC) are set at 0.3 for T, 0.4 for I, and 0.3 for F, indicating that a low level of Life Cycle Cost is desirable, but some level of inconsistency and falsity is also acceptable. The ideal values for Carbon Footprint (CL) are set at 0.6 for T, 0.3 for I, and 0.1 for F, indicating that a low level of Carbon Footprint is desirable, but some level of inconsistency and falsity is also acceptable. These ideal values can be used to compare the performance of different technologies, such as VRF and Li-ion batteries, based on their weighted neutrosophic values for each criterion.

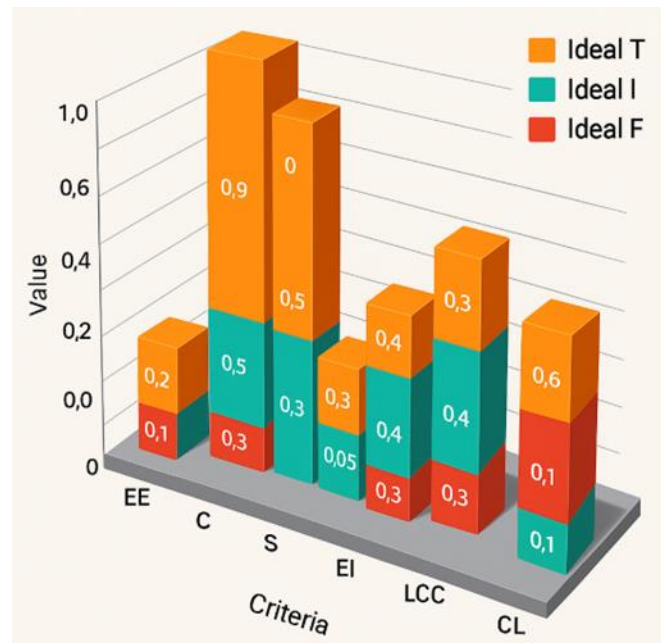


Figure 24. Balancing Truth, Uncertainty, and Negativity: A Neutrosophic Framework for Ideal BESS Performance.

3. Calculating Euclidean Distances for BESS Technologies

To calculate the Euclidean distance between each BESS technology and the ideal solution, we first need to determine the weighted neutrosophic values for each technology· these values represent the weighted average of the truth, indeterminacy, and falsity components of each criterion·

Steps: · Assign weights: We assign weights to each criterion based on their importance. This can be done through expert opinion or other techniques.

- Calculate weighted neutrosophic values: We multiply the neutrosophic values for each criterion by their corresponding weights and then sum the weighted values for each component (truth, indeterminacy, falsity) to obtain the weighted neutrosophic value for the technology.
- Calculate Euclidean distance: We use the formula for Euclidean distance to calculate the distance between each technology's weighted neutrosophic values and the ideal solution.

$$\text{Formula: } \text{Dist}_{xy} = \sqrt{\sum_{k=1}^m (X_{ik} - X_{jk})^2}$$

Table 14. Li-ion: Criteria (Weighted Neutrosophic Value, Ideal Value, Distance).

Criteria	Weighted Neutrosophic Value	Ideal Value	Distance
EE	0.21	0.8	0.671
C	0.12	0.2	0.12
S	0.18	0.9	0.122
EI	0.105	0.9	0.141
LCC	0.045	0.3	0.234
CL	0.03	0.6	0.291

Total Distance: 1.569. Based on the weighted neutrosophic values and ideal values presented in Table 4 for Li-ion batteries, it can be seen that Li-ion batteries have some distance from the ideal criteria values in all criteria except for Safety, where the distance is very small. The total distance from the ideal criteria values is relatively high at 1.569. This indicates that Li-ion batteries have some room for improvement in terms of Energy Efficiency, Cost, Environmental Impact, and Life Cycle Cost. In particular, Li-ion batteries have a relatively large distance from the ideal criteria values in Energy Efficiency and Life Cycle Cost, suggesting that improving these criteria could have a significant impact on the overall performance of Li-ion batteries.

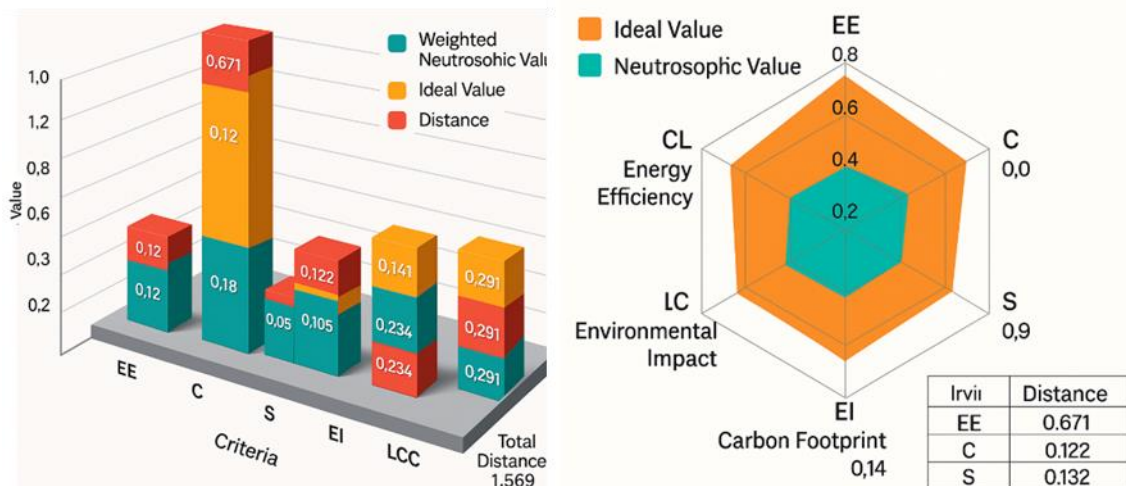


Figure 25. Li-ion Battery Evaluation: Neutrosophic vs. Ideal Performance across Key Criteria.

- Analysis of VRF System Performance Based on Weighted Neutrosophic Evaluation
 1. As illustrated in Table 15, the weighted neutrosophic values for each criterion reveal discrepancies between current VRF system performance and the established ideal benchmarks. Notably, the systems exhibit significant shortfalls across multiple categories, with the exception of Safety (S), where performance approaches the ideal.
 2. The cumulative deviation from ideal values, quantified as 1.385, underscores critical areas requiring targeted improvement. The most pronounced gaps occur in Energy Efficiency (EE) and Life Cycle Cost (LCC), with distances of 0.707 and 0.208, respectively. These metrics suggest that enhancing these dimensions would yield substantial gains in overall system efficacy. Additionally, moderate discrepancies in Cost (C) (0.02) and Environmental Impact (EI) (0.041) indicate further opportunities for optimization, where these findings emphasize the need for prioritizing technological and operational advancements in energy management and lifecycle cost reduction to align VRF systems more closely with ideal performance standards.

Table 15. VRF Criteria (Weighted Neutrosophic Value, Ideal Value, and Distance).

Criteria	Weighted Neutrosophic Value	Ideal Value	Distance
EE (Energy Efficiency)	0.175	0.8	0.707
C (Cost)	0.18	0.2	0.02
S (Safety)	0.16	0.9	0.132
EI (Environmental Impact)	0.135	0.9	0.041
LCC (Life Cycle Cost)	0.06	0.3	0.208
CL (Comfort Level)	0.025	0.6	0.277

Total Distance: 1.385

From the weighted neutrosophic values and ideal values shown in Table 15, it is evident that VRF systems are falling short of ideal standards in most categories, with the exception of Safety (S), where they are close to the ideal. The total difference from the ideal values is 1.385, which highlights areas where improvements can be made, particularly in Energy Efficiency (EE), Cost (C), Environmental Impact (EI), and Life Cycle Cost (LCC). Specifically, the biggest gaps are in Energy Efficiency (EE) and Life Cycle Cost (LCC), indicating that improvements in these areas could significantly enhance overall performance.

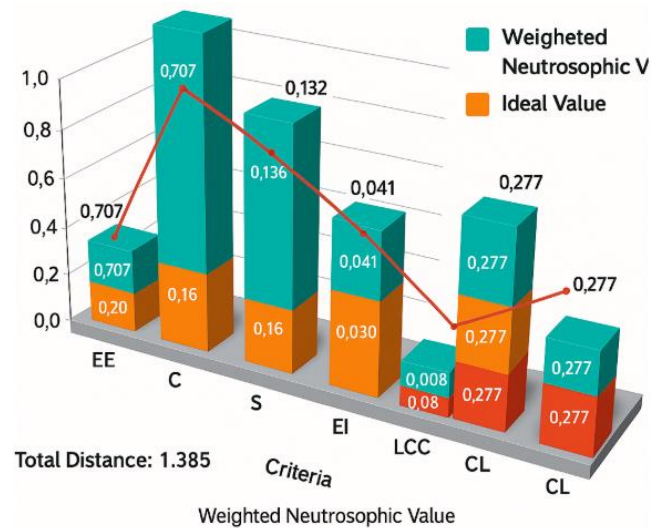


Figure 26. VRF Close Encounters with the Ideal, Measured by Neutrosophic Distances.

- Performance Evaluation of Na-ion Batteries Using Weighted Neutrosophic Assessment

This table gives us the weighted neutrosophic values, ideal benchmarks, and Euclidean distances for Na-ion batteries across key criteria, and the data reveals notable deviations from optimal performance in all categories except Safety (S), where the discrepancy is marginal, with computed distance: 0.149), where the total Euclidean distance (1.721) quantifies the cumulative divergence from ideal conditions, highlighting critical areas for improvement, where the most substantial gaps occur in Energy Efficiency (EE) (0.75) and Life Cycle Cost (LCC) (0.165), we suggesting that advancements in these domains would significantly elevate overall performance. Added that, moderate deviations in Cost (C) (0.24) and Environmental Impact (EI) (0.132) further underscore opportunities for optimization.

Comparative Analysis

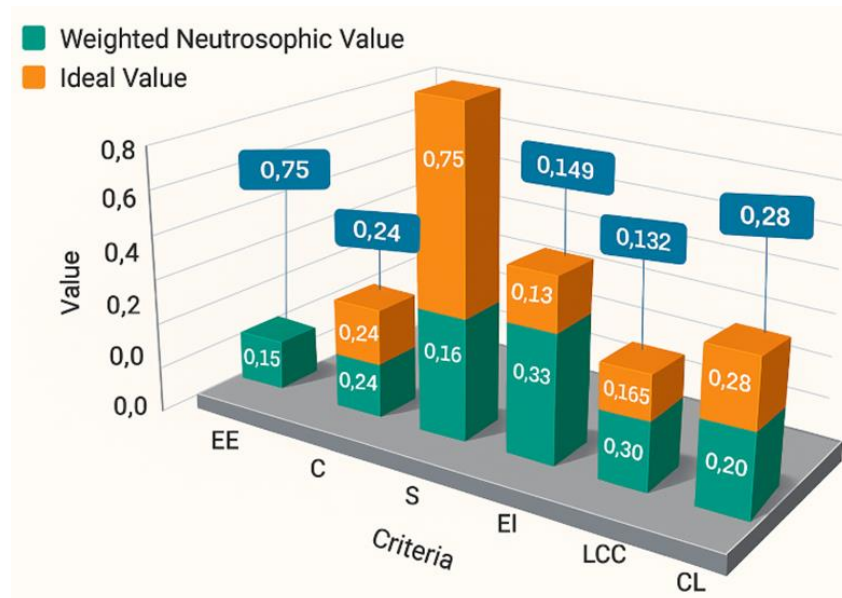
Lower Euclidean distances indicate superior alignment with ideal solutions, and In this context, by the VRF systems (1.385) demonstrate the closest adherence to ideal performance, the Li-ion batteries (1.569) follow, exhibiting intermediate performance, and the Na-ion batteries (1.721) currently rank furthest from the ideal, necessitating targeted enhancements, particularly in energy efficiency and lifecycle cost management, such that these findings advocate for prioritizing research and development in energy density and cost reduction to bridge the performance gap in Na-ion battery.

Table 16. Na-ion: Criteria (Weighted Neutrosophic Value, Ideal Value, and Distance) for Na-ion.

Criteria	Weighted Neutrosophic Value	Ideal Value	Distance
EE	0.15	0.8	0.75
C	0.24	0.2	0.24
S	0.14	0.9	0.149
EI	0.12	0.9	0.132
LCC	0.075	0.3	0.165
CL	0.02	0.6	0.28

Total Distance: 1.721. Based on the weighted neutrosophic values and ideal values presented in Table 6, it is clear that Na-ion batteries are somewhat distant from the ideal criteria values in all areas except for Safety (S), where the gap is minimal. The total distance from the ideal values is 1.721, indicating that Na-ion batteries have room for improvement in Energy Efficiency (EE), Cost (C), Environmental Impact (EI), and Life Cycle Cost (LCC). Notably, Na-ion batteries show a significant gap in Energy Efficiency (EE) and Life Cycle Cost (LCC). Focusing on improving these areas could notably enhance the overall performance of Na-ion batteries.

Interpretation: Lower Euclidean distances indicate closer proximity to the ideal solution, suggesting better performance. In this example, VRF has the lowest distance (1.385) and therefore the closest match to the ideal solution, followed by Li-ion (1.569) and Na-ion (1.721) .

**Figure 27.** Na-ion - An Equally Strong Contender? Exploring Performance Gaps through Neutrosophic Distances.

5.5 | Neutrosophic Decision Matrix for Evaluating BESS: Focusing on Energy Efficiency, Cost, Safety, and More

Table 17. Decision Matrix for Evaluating BESS Technologies Using Neutrosophic Sets and Compromise Solution Method.

Criteria	Weight	Li-ion (T, I, F)	VRF (T, I, F)	Na-ion (T, I, F)
Energy Efficiency (EE)	0.25	(0.8, 0.1, 0.1)	(0.7, 0.2, 0.1)	(0.6, 0.3, 0.1)
Cost (C)	0.20	(0.2, 0.5, 0.3)	(0.3, 0.4, 0.3)	(0.4, 0.3, 0.3)
Safety (S)	0.20	(0.9, 0.05, 0.05)	(0.8, 0.1, 0.1)	(0.7, 0.2, 0.1)
Environmental Impact (EI)	0.15	(0.7, 0.2, 0.1)	(0.9, 0.05, 0.05)	(0.8, 0.1, 0.1)
Life Cycle Cost (LCC)	0.15	(0.3, 0.4, 0.3)	(0.4, 0.3, 0.3)	(0.5, 0.2, 0.3)
Cycle Life (CL)	0.05	(0.6, 0.3, 0.1)	(0.5, 0.4, 0.1)	(0.4, 0.5, 0.1)

From the decision matrix in Table 17, it is clear that Li-ion batteries lead the way in Energy Efficiency (EE), outperforming both VRF and Na-ion batteries. They show higher truth-values (T) and lower uncertainty (I) and falsity (F) values, which means they perform better overall in this category. However, Li-ion batteries have a shorter cycle life, which results in needing more frequent replacements. In terms of safety, Li-ion batteries excel, with high truth-values (T) and low uncertainty (I) and falsity (F) values, making them safer than both VRF and Na-ion batteries. When looking at costs (C), Li-ion batteries have lower falsity (F) values than VRF and Na-ion, but their higher uncertainty (I) values suggest they are less predictable regarding cost-effectiveness. This is indicated by their relatively low truth (T) values for cost, showing uncertainty about long-term expenses. For environmental impact (EI), Li-ion batteries exhibit higher falsity (F) values, largely due to high uncertainty (I) related to their cycle life. The shorter cycle life contributes to environmental issues as it leads to more frequent extraction of raw materials, especially compared to batteries with longer cycle lives like VRF and Na-ion. Finally, when it comes to life cycle cost (LCC), Li-ion batteries have lower falsity (F) values than VRF and Na-ion batteries. However, their higher uncertainty (I) values indicate that predicting their long-term cost-effectiveness is challenging, due to lower truth (T) values in this aspect.

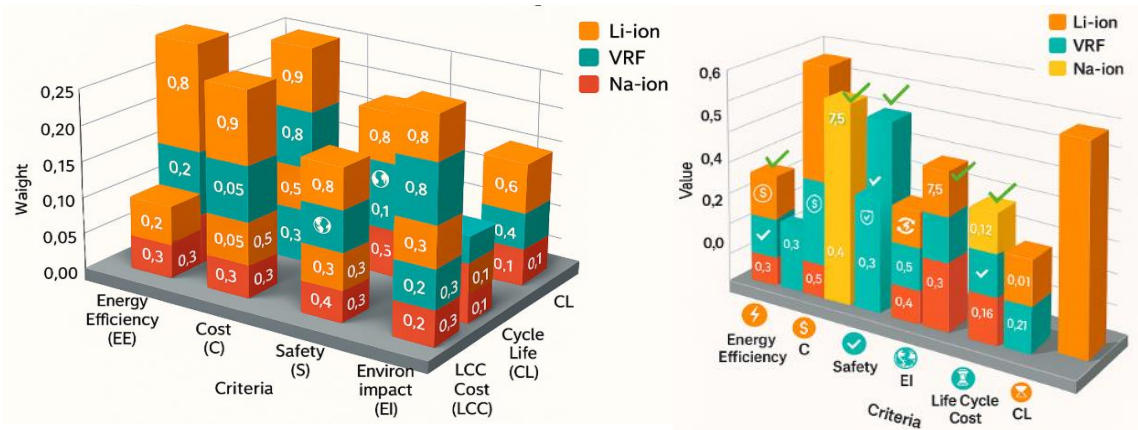


Figure 28. Understanding Uncertainty in BESS Evaluation: A Neutrosophic Matrix Reveals Truth, Indeterminacy, and Falsity.

5.6 | Comparative Evaluation of BESS Technologies by using Weighted Neutrosophic Analysis

This section presents us the systematic evaluation of Battery Energy Storage Systems (BESS) technologies Li-ion, VRF, and Na-ion based on weighted neutrosophic values across multiple criteria, where the neutrosophic values (T, I, F), representing truth, indeterminacy, and falsity degrees, are weighted to reflect both performance and criterion importance, ensuring a comprehensive assessment.

Weighted Neutrosophic Values for BESS Technologies

Table 18 summarizes the derived weighted neutrosophic values for each technology-criterion pair:

Table 18. Weighted Neutrosophic Values (T, I, F) for BESS Technologies.

Criteria	Li-ion	VRF	Na-ion
Energy Efficiency (EE)	(0.2, 0.025, 0.025)	(0.175, 0.05, 0.025)	(0.15, 0.075, 0.025)
Cost (C)	(0.04, 0.1, 0.06)	(0.06, 0.08, 0.06)	(0.08, 0.06, 0.06)
Safety (S)	(0.18, 0.01, 0.01)	(0.16, 0.02, 0.02)	(0.14, 0.04, 0.02)
Environmental Impact (EI)	(0.105, 0.03, 0.015)	(0.135, 0.0075, 0.0075)	(0.12, 0.015, 0.015)
Life Cycle Cost (LCC)	(0.045, 0.06, 0.045)	(0.06, 0.045, 0.045)	(0.075, 0.03, 0.045)

Cycle Life (CL)	(0.03, 0.015, 0.005)	(0.025, 0.02, 0.005)	(0.02, 0.025, 0.005)
------------------------	----------------------	----------------------	----------------------

Steps for Calculation

- Multiply each part of the neutrosophic values (T, I, F) by its respective weight for each criterion and technology.
- Add the weighted values (weighted T, weighted I, and weighted F) for each criterion and technology to get the final weighted neutrosophic value.

Example Calculation for Li-ion and Energy Efficiency (EE):

- For the uncertainty (I): Weighted I = $0.25 \times 0.1 = 0.025$
- For the falsity (F): Weighted F = $0.25 \times 0.1 = 0.025$

So, the weighted neutrosophic value for Li-ion regarding Energy Efficiency (EE) is (0.2, 0.025, 0.025). These weighted values take into account both the performance of each technology and the importance of each criterion, resulting in a more thorough evaluation.

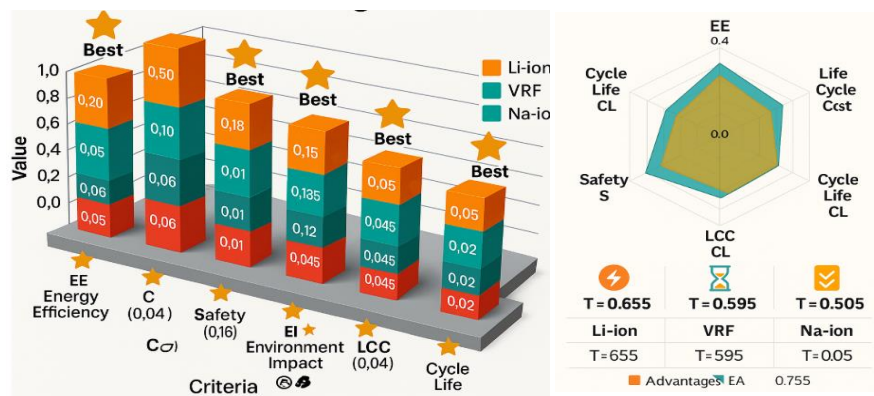


Figure 29 (a). Neutrosophic Representation of Criteria for Comprehensive Decision-Making.

Figure 29 (b). Comparative Analysis of Truth Values for BESS Technologies Using Neutrosophic Evaluation.

5.7 | Defining Ideal Performance: Neutrosophic Targets for BESS Technologies

The closer the technology value is to these ideal solutions, the better it meets the desired criteria. The following is the ideal solution for each criterion in this example:

Table 19. Ideal Criteria (T, I, F) Values.

Criteria	Ideal T	Ideal I	Ideal F
EE	0.8	0.1	0.1
C	0.2	0.5	0.3
S	0.9	0.05	0.05
EI	0.9	0.05	0.05
LCC	0.3	0.4	0.3
CL	0.6	0.3	0.1

The ideal values for each criterion, as shown in Table 9, represent the optimal performance levels for Energy Efficiency (EE), Cost (C), Safety (S), Environmental Impact (EI), Life Cycle Cost (LCC), and Cycle Life (CL).

For instance, Energy Efficiency (EE) has an ideal truth (T) value of 0.8, with low ideal indeterminacy (I) and falsity (F) values of 0.1 each. This indicates that the goal is to achieve high-energy efficiency, with minimal uncertainty and falsehoods.

Similarly, Safety (S) has an ideal truth (T) value of 0.9, along with low ideal values for indeterminacy (I) and falsity (F) at 0.05 each. This implies that the aim is to ensure high safety while keeping uncertainty and inaccuracies to a minimum. In addition, the ideal value for Cycle Life (CL) is 0.6, with lower ideal values of 0.3 for uncertainty and 0.1 for inaccuracy. This suggests that having a longer cycle life along with minimal uncertainty and inaccuracies is the desired goal.

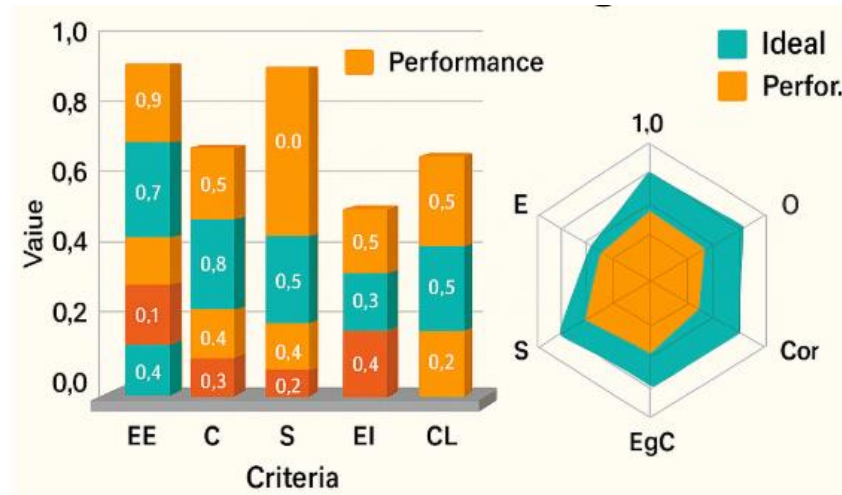


Figure 30. Comparison of Ideal T, I, and F Values for Multiple Criteria.

Our ideal values for each criterion represent the optimal performance targets in the evaluation of Battery Energy Storage Systems (BESS) Technologies. The performance values reflect the actual degree to which each technology meets these targets.

5.8 | Selecting the Best Choice: Ranking BESS Technologies Using Euclidean Distances

Euclidean Distance: This metric measures the "distance" between each BESS technologies weighted neutrosophic values (Truth, Indeterminacy, Falsity) and the ideal solution based on the defined criteria.

This table shows the outcomes of ranking analysis of BESS technologies according to the Euclidean distance from the ideal solution.

Table 20. shows the type of measurement used to compare neutrosophic values.

Technology	Euclidean Distance	Ranking	Truth (T)	Indeterminacy (I)	Falsity (F)
VRF	1.385	1 (Best)	[0.8, 0.9]	[0.1, 0.2]	[0.1, 0.2]
Li-ion	1.569	2	[0.7, 0.8]	[0.15, 0.25]	[0.2, 0.3]
Na-ion	1.721	3	[0.6, 0.7]	[0.2, 0.3]	[0.3, 0.4]

Calculate Compromise Score:

We Use the equation:

$$CS = \frac{WSS + \lambda \cdot WUS}{1 + \lambda} - WDS$$

Where:

- WSS: Weighted Satisficing Score (aggregated performance under certainty).
- WUS: Weighted Uncertainty Score (penalty for indeterminacy in criteria).
- WDS: Weighted Dissatisficing Score (penalty for criteria non-fulfillment).

- λ : Trade-off parameter $\lambda \in [0,1]$ balancing satisficing (WSS) against uncertainty (WUS).

Interpretation of λ

- Higher λ ($\rightarrow 1$): Prioritizes satisficing (performance) over uncertainty reduction.
- Lower λ ($\rightarrow 0$): Emphasizes minimizing uncertainty, accepting lower performance.

Rank Technologies:

For each technology, achieve a list of those technologies ordered by their Compromise Score in descending order. The technology with the highest rating represents an overall solution with a degree of satisfaction, dissatisfaction, and uncertainty.

Ranking: With the smallest Euclidean distance (1.385), the closest proximity to the ideal solution is VRF technology.

Neutrosophic Values: Truth (T): [0.8, 0.9] - Indicates a high degree of membership; somewhat aligned with the desired criteria. Identification (A): [0.1, 0.2] - Moderate uncertainty.

Falsity (F): [0.1, 0.2] - Degree of non-membership (considered low), therefore degree of deviation from ideal conditions is negligible. VRF: With the lowest Euclidean distance, VRF appears to be the most aligned with the ideal solution based on the given criteria and their weights.

Li-ion: At a ratio of (1.569) Li-ion technology demonstrates a little deviation from the ideal.

Neutrosophic Values: Truth (T): [0.7, 0.8]- Moderate degree of membership

Indeterminacy (I): [0.15, 0.25] - Higher level of uncertainty.

False (F): [0.2, 0.3] - Intermediate non-membership.

Li-ion and Na-ion: Show increasing distances from the ideal solution, suggesting a gradual decrease in their overall suitability.

Na-ion: Na-ion technology (1.721) shows the largest distance from the ideal solution.

Neutrosophic Values: Truth (T): [0.6, 0.7] Less membership degree.

Indeterminacy (I): [0.2, 0.3] $t \rightarrow [0.1, 0.3]$ [5] Higher uncertainty.

Falsity (F) [0.3, 0.4] = Larger degree of non-membership with respect to desired criteria, suggesting greater distance with respect to desired criteria

6 | Conclusion

In this study we propose a novel, global approach for assessing battery energy storage systems (BESS) taking neutrosophic sets and compromise solutions into account, hence covering the aspects of uncertainty and imprecision.

- More Accurate Evaluation of BESS Performance: While BESS evaluation is done under vague conditions, neutrosophic assessment contributes to a more accurate evaluation approach as it takes into account flexible ranges of truth, false and indeterminate values.
- Balanced Decision-Making: The middle ground helps mitigate uncertainty in the decision-making process by enabling consideration of both praise and blame in terms of how various decision-makers prefer the outcomes.
- This framework is versatile, suitable for various BESS technologies, evaluation criteria, and decision-making contexts, ensuring broad applicability.

6.1 | Key Findings

- The methodology compared three BESS technologies (Li-ion, VRF, and Na-ion) on six criteria and produced a straightforward ranking based on the preferences and risk appetite of decision-makers.
- To facilitate decision-making, results were effectively presented in visualization tools such as bar charts, graphs etc.

6.2 | Future Research

- Enhancing methods for dealing with uncertainty through neutrosophic logic.

Funding

This research has no funding source.

Data Availability

The datasets generated during and/or analyzed during the current study are not publicly available due to the privacy-preserving nature of the data but are available from the corresponding author upon reasonable request.

Conflicts of Interest

The authors declare that there is no conflict of interest in the research.

Ethical Approval

This article does not contain any studies with human participants or animals performed by any of the authors.

References

- [1] Qie, X.; Zhang, R.; Hu, Y.; Sun, X.; Chen, X. A Multi-Criteria Decision-Making Approach for Energy Storage Technology Selection Based on Demand. *Energies* 2021, 14, 6592.
- [2] Mishra, A.R.; Tripathi, D.K.; Cavallaro, F.; Rani, P.; Nigam, S.K.; Mardani, A. Assessment of Battery Energy Storage Systems Using the Intuitionistic Fuzzy Removal Effects of Criteria and the Measurement of Alternatives and Ranking Based on Compromise Solution Method. *Energies* 2022, 15, 7782.
- [3] Zubiria, A.; Menéndez, Á.; Grande, H.-J.; Meneses, P.; Fernández, G. Multi-Criteria Decision-Making Problem for Energy Storage Technology Selection for Different Grid Applications. *Energies* 2022, 15, 7612.
- [4] Zhang HY, Wang JQ, Chen XH. Interval neutrosophic sets and their application in multicriteria decision making problems. *Scientific World Journal*. 2014 Feb 17; 2014:645953.
- [5] Lopez S, Akizu-Gardoki O, Lizundia E. Comparative life cycle assessment of high performance lithium-sulfur battery cathodes. *J Clean Prod*. 2021 Feb 1; 282:124528.
- [6] Carvalho, M.L.; Mela, G.; Temporelli, A.; Brivio, E.; Girardi, P. Sodium-Ion Batteries with Ti1Al1TiC1.85 MXene as Negative Electrode: Life Cycle Assessment and Life Critical Resource Use Analysis. *Sustainability* 2022, 14, 5976.
- [7] Hill, N., Rauei, M. et al. 2023, Research for TRAN Committee – Environmental challenges through the life cycle of battery electric vehicles, European Parliament, Policy Department for Structural and Cohesion Policies, Brussels.
- [8] Mathew Aneke et al. Energy storage technologies and real life applications - a state of the art review *Appl Energ* (2016).
- [9] Dehghani-Sanij AR, Tharumalingam E, Dusseault MB, Fraser R. Study of energy storage systems and environmental challenges of batteries. *Renew Sustain Energy Rev* 2019; 104: 192 – 208. .
- [10] Holger C, Michael S., Kucevic D., Jossen A. Lithium-Ion Battery Storage for the Grid A Review of Stationary Battery Storage System Design Tailored for Applications in Modern Power Grids. *Energies* 2017; 10.
- [11] Krishan O., Suhag S. An updated review of energy storage systems: Classification and applications in distributed generation power systems incorporating renewable energy resources. *Int J Energy Res* 2018; 1 – 40.
- [12] Rani, P.; Ali, J.; Krishankumar, R.; Mishra, A.R.; Cavallaro, F.; Ravichandran, K.S. An Integrated Single-Valued Neutrosophic Combined Compromise Solution Methodology for Renewable Energy Resource Selection Problem. *Energies* 2021, 14, 4594.

- [13] Broumi, S., Talea, M., Bakali, A., Smarandache, F., Nagarajan, D., Lathamaheswari, M., & Parimala, M. (2019). Shortest path problem in fuzzy, intuitionistic fuzzy and neutrosophic environment: an overview. *Complex & Intelligent Systems*, 5, 371-378.
- [14] Broumi, S., Nagarajan, D., Bakali, A., Talea, M., Smarandache, F., Lathamaheswari, M., & Kavikumar, J. (2019). Implementation of neutrosophic function memberships using MATLAB program. *Infinite Study*.
- [15] Salama, A. A., & Smarandache, F. (2014). Neutrosophic crisp set theory. *Neutrosophic Sets and Systems*, 5, 27-35.
- [16] Salama, A. A., El-Ghareeb, H. A., Manic, A. M., & Smarandache, F. (2014). Introduction to develop some software programs for dealing with neutrosophic sets. *Neutrosophic Sets and Systems*, 3, 51-52.
- [17] Elwahsh, H., Gamal, M., Salama, A., & El-Henawy, I. (2018). A novel approach for classifying MANETs attacks with a neutrosophic intelligent system based on genetic algorithm. *Security and Communication Networks*, 2018, 1-7.
- [18] ElWahsh, H., Gamal, M., Salama, A., & El-Henawy, I. (2018). Intrusion detection system and neutrosophic theory for MANETs: A comparative study. *Neutrosophic Sets and Systems*, 23, 16-22.
- [19] Ibrahim Yasser, A., Twakol, A., Abd El-Khalek, A. A., Samrah, A., & Salama, A. A. (2020). COVID-X: Novel health-fog framework based on neutrosophic classifier for confrontation Covid-19. *Neutrosophic Sets and Systems*, 35, 1-21.
- [20] Amin, B., Salama, A. A., El-Henawy, I. M., Mahfouz, K., & Gafar, M. G. (2021). Intelligent neutrosophic diagnostic system for cardiocography data. *Computational Intelligence and Neuroscience*, 2021(1), 6656770.
- [21] Alhasan, K. F., Salama, A. A., & Smarandache, F. (2021). Introduction to neutrosophic reliability theory. *International Journal of Neutrosophic Science*, 15(1), 52-61.
- [22] Ibrahim Yasser, A., Abd El-Khalek, A. A., Twakol, A., Abo-Eldin, M. E., Salama, A. A., & Khalifa, F. (2021). A hybrid automated intelligent COVID-19 classification system based on neutrosophic logic and machine learning techniques using chest X-ray images. In *Advances in Data Science and Intelligent Data Communication Technologies for COVID-19* (Vol. 378). Springer Nature.
- [23] Salama, A. A., Tarek, Z., Darwish, E. Y., Elseuof, S., & Shams, M. Y. (2024). Neutrosophic Encoding and Decoding Algorithm for ASCII Code System. *Neutrosophic Sets and Systems*, 63, 105-129.
- [24] Khalid, H. E., Sabbagh, R., Salma, A. A., Thanoon, T. Y., & Elagamy, H. A. (2023). Novel Neutrosophic Objects Within Neutrosophic Topology. *Neutrosophic Sets and Systems*, 61(1), 15.
- [25] Essa, A. K., Sabbagh, R., Salama, A. A., Khalid, H. E., Aziz, A. A. A., & Mohammed, A. A. (2023). An overview of neutrosophic theory in medicine and healthcare. *Neutrosophic Sets and Systems*, 61(1), 13.
- [26] A. A. Salama, Hewayda ElGhawalby, Huda E. Khalid, Ahmed K. Essa, Ahmed A. Mohammed, *Neutrosophic Algebraic Mathematical Morphology*, *Neutrosophic Sets and Systems*, Vol. 61, 2023, pp. 426-464.
- [27] Salama, A.A., Bhatnagar, R., Alharthi, N.S., Tolba, R.E., Shams, M.Y. (2023). Neutrosophic Fuzzy Data Science and Addressing Research Gaps in Geographic Data and Information Systems. In: Dao, NN., Thinh, T.N., Nguyen, N.T. (eds) *Intelligence of Things: Technologies and Applications. ICIT 2023. Lecture Notes on Data Engineering and Communications Technologies*, vol 187. Springer, Cham.
- [28] Essa, Ahmed K., Montifort Blessings Andrew Mitungwi, Tuweh Prince Gadama, and A. A. Salama. 2023. "Neutrosophic Inference System (NIS) in Power Electrical Transformers Adapted the MIL-STD-1629A." *Neutrosophic Sets and Systems* 58 (2023): 25-67.
- [29] Kamal, B., Khalid, H. E., Salama, A. A., & El-Baghdady, G. I. (2023). Finite Difference Method for Neutrosophic Fuzzy Second Order Differential Equation under Generalized Hukuhara Differentiability. *Neutrosophic Sets and Systems*, 58(1), 19.
- [30] Alhabib, R., Alhabib, A., & Salama, A. A. (2023). Neutrosophic Price Indices with an Applied Study on Pesticide Prices. *Neutrosophic Sets and Systems*, 58, 603-610.
- [31] Jdid, M., Alhabib, R., & Salama, A. A. (2023). The basics of neutrosophic simulation for converting random numbers associated with a uniform probability distribution into random variables follow an exponential distribution. *Neutrosophic Sets and Systems*, 53(1), 22.
- [32] Smarandache, F. (2002). A unifying field in logics: Neutrosophic logic. *Neutrosophy, neutrosophic set, neutrosophic probability, and neutrosophic statistics. Multiple-Valued Logic*, 8(3), 297-384.
- [33] M AlZubi, M., A Mohamed, M., Amer, H. M., & Salama, A. A. (2024). Neutrosophic Fuzzy Power Management (NFPM): Tackling Uncertainty in Energy Harvesting for Sensor Networks. *Neutrosophic Sets and Systems*, 76(1), 6.

Disclaimer/Publisher's Note: The perspectives, opinions, and data shared in all publications are the sole responsibility of the individual authors and contributors, and do not necessarily reflect the views of Sciences Force or the editorial team. Sciences Force and the editorial team disclaim any liability for potential harm to individuals or property resulting from the ideas, methods, instructions, or products referenced in the content.