



# Assessment of Lithium-Ion Battery Types by Multi-Criteria Decision Making

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## ABSTRACT

Lithium-ion batteries are the dominant energy storage technology for a wide range of applications, from portable electronics to electric vehicles and grid-scale energy storage. However, the diverse applications present conflicting demands on battery performance, leading to the development of numerous lithium-ion battery chemistries with distinct advantages and disadvantages. Choosing the optimal battery type for a specific application becomes a complex Multi-Criteria Decision-Making (MCDM) problem. This paper utilizes a MCDM framework to assess the performance of six common lithium-ion battery types: Lithium Cobalt Oxide (LCO), Lithium Manganese Oxide (LMO), Lithium Nickel Manganese Cobalt Oxide (NMC), Lithium Iron Phosphate (LiFePO<sub>4</sub>) and Lithium Titanate Oxide (Li<sub>4</sub>Ti<sub>5</sub>O<sub>12</sub>). The assessment considers technical criteria such as specific energy, specific power, cycle life, calendar life, safety, and environmental impact, alongside economic criteria like cost and availability. Through quantitative analysis and a weighted aggregation approach, the MCDM framework ranks the battery types based on their suitability for different application categories. The paper highlights the trade-offs and synergies between various criteria, providing valuable insights for engineers, researchers, and decision-makers navigating the diverse landscape of lithium-ion battery technology.

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## 1. Introduction

Lithium-ion batteries have revolutionized energy storage with their high energy density, long cycle life, and efficient charge/discharge cycles. Their versatility has propelled them into the forefront of portable electronics, electric vehicles, grid-scale energy storage, and numerous other applications [1-3]. However, the demands of each application differ significantly. Portable devices prioritize high energy density for extended operation, while electric vehicles require a balance

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between energy density, power delivery, and cycle life. Grid-scale applications, on the other hand, emphasize safety, durability, and cost-effectiveness [3,4].

This inherent variety in application demands has led to the development of numerous lithium-ion battery chemistries, each with unique strengths and weaknesses. Lithium Cobalt Oxide (LCO) offers high energy density but suffers from limited cycle life and thermal instability. Lithium Iron Phosphate (LFP) boasts excellent cycle life and safety but comes with lower energy density. Lithium Nickel Manganese Cobalt Oxide (NMC) strikes a balance between energy density, power delivery, and cycle life, making it popular for electric vehicles. The landscape is further complicated by emerging chemistries like Lithium Titanate Oxide (LTO) with exceptional cycle life and Nickel Cobalt Aluminum Oxide (NCA) with high power density [5,6].

Choosing the optimal battery type for a specific application becomes a complex multi-criteria decision-making problem. Balancing technical criteria like specific energy, specific power, cycle life, calendar life, safety, and environmental impact alongside economic considerations like cost and availability requires a systematic and holistic approach (see Figure 1) [7-10].



**Figure 1:** Lithium-ion battery types.

This research is arranged into five sections. Section 2 defines the literature review and recent studies in area of assessing of lithium-ion battery types by multi-criteria decision making and tries to show the gap in research. Section 3 suggests methodology for calculation. Section 4 proposes

the results of this research. Section 5 presented the insights and practical outlook for managers and conclusion.

## 2. Literature review

Extensive research has been conducted on the performance characteristics of various lithium-ion battery chemistries. Studies have compared energy density, cycle life, and power delivery under different operating conditions and aging profiles [10-11]. The safety aspects of different chemistries, including thermal stability and abuse tolerance, have also been investigated [12,13]. Environmental impacts and life cycle assessments have become increasingly important, with studies analyzing the resource consumption, greenhouse gas emissions, and recyclability of various battery materials [14,15].

However, few studies employ a comprehensive MCDM framework to assess and rank different lithium-ion battery types for specific applications. Most research focuses on individual aspects like cycle life or cost analysis, failing to address the complex interplay between multiple criteria. Some MCDM applications in the broader context of energy storage include selecting battery energy storage systems for grid applications [16-18] or choosing energy storage technologies for different grid services [19-22]. However, these studies either focus on broader technology categories or do not delve deeply into the nuances of different lithium-ion battery chemistries [15,16].

This paper addresses this gap by applying a systematic MCDM framework to assess six common lithium-ion battery types for various application categories. The framework considers both technical and economic criteria, providing a comprehensive understanding of the trade-offs and synergies between different priorities.

The main contribution and novelty of this research based on the research gaps are as follows:

- Assessment of lithium-ion battery types by multi-criteria decision making.

**Table 1:** Survey of related works.

References	Application	Approach
Loganathan et al [1]	Li-Ion batteries used in electric vehicles	MCDM method
Zhao et al [3]	Assessment for battery energy storage systems	Fuzzy- MCDM

References	Application	Approach
Tajik et al [5]	Sustainable cathode material selection in lithium-ion batteries using	A novel hybrid MCDM
Guan et al [7]	Evaluating batteries for renewable energy storage:	A hybrid MCDM framework based on combined objective weights and uncertainty-preserved COPRAS
Li et al [9]	Select the optimal electrochemical energy storage planning program	A hybrid MCDM method
This research	Select lithium-ion battery	A hybrid MCDM framework

### 3. Solution Methodology

There are several criteria that can be considered when evaluating different types of lithium-ion batteries. These criteria include energy density, power density, cycle life, safety, cost, and environmental impact [22-25].

To make a decision on the best lithium-ion battery type, MCDM methods can be used. MCDM methods allow for the consideration of multiple criteria and the weighting of their importance to arrive at a decision [26-28].

One MCDM method that can be applied is the Analytic Hierarchy Process (AHP). AHP involves breaking down the decision problem into a hierarchy of criteria and alternatives, and then assessing the relative importance of each criterion through pairwise comparisons. The pairwise comparisons can be done by experts or stakeholders who have knowledge and experience in the field of lithium-ion batteries [28-30].

For example, in the case of evaluating lithium-ion battery types, the hierarchy could be structured as follows:

Level 1: Criteria

- Energy density
- Power density
- Cycle life

- Safety
- Cost
- Environmental impact

Level 2: Alternatives

- Lithium nickel manganese cobalt oxide (NMC)
- Lithium iron phosphate (LiFePO<sub>4</sub>)
- Lithium cobalt oxide (LCO)
- Lithium manganese oxide (LMO)
- Lithium titanate (Li<sub>4</sub>Ti<sub>5</sub>O<sub>12</sub>)

Experts or stakeholders would then provide pairwise comparisons between the criteria and alternatives, indicating their relative importance. These comparisons can be transformed into numerical values using the Saaty scale or other scales [30].

Once the pairwise comparisons are completed, the AHP method calculates the priority weights for each criterion and alternative. These weights reflect the relative importance of each criterion or alternative in the decision-making process.

Using these priority weights, the decision-maker can then evaluate and rank the lithium-ion battery types based on their performance across the criteria.

Other MCDM methods that can be used for this decision-making process include the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) and the Preference Ranking Organization Method for Enrichment Evaluation (PROMETHEE).

Overall, using MCDM methods like AHP can help in selecting the most suitable lithium-ion battery type based on the specific requirements and priorities of the decision-maker.

This section describes the methodology adopted to evaluate lithium-ion battery types using MCDM methods. The selected MCDM techniques are discussed, along with the criteria identified for the decision-making process. The data collection and analysis procedures are also elucidated to ensure transparency and replicability of the research (see Figure 2) [30-32].

1. Problem Definition:

- Clearly define the objective of the study, which is to assess lithium-ion battery types using MCDM methods
- Specify the criteria and factors to be considered in the decision-making process [22-25].

2. Data Collection:

- Gather relevant data and information pertaining to the identified criteria and factors.
- Use a combination of primary and secondary sources, such as field surveys, environmental assessments, economic data, and expert interviews, to ensure comprehensive data collection.
- Ensure data accuracy, reliability, and consistency to make valid and informed decisions [25-28].

3. Selection of MCDM Method:

- Choose the appropriate MCDM method(s) that best aligns with the objectives of the study and the nature of the decision problem.
- Popular MCDM methods for renewable energy location decisions include Analytic Hierarchy Process (AHP), Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS), Preference Ranking Organization Method for Enrichment Evaluation (PROMETHEE), and others.
- Justify the selection of the chosen MCDM method(s) based on their ability to handle multiple criteria, uncertainty, and trade-offs.

4. Criteria Weighting:

- Assign weights to each criterion based on their relative importance in the decision-making process.
- Utilize expert opinions, literature review, and stakeholder consultations to determine the weights.

- Apply the selected MCDM method(s) to calculate the relative weights or importance of each criterion [29-30].

5. Data Normalization:

- Normalize the collected data to ensure that different criteria are on the same scale and have consistent units.
- Consider normalization techniques such as min-max normalization or z-score normalization.
- Normalize both quantitative and qualitative data, ensuring their compatibility for analysis.

6. Decision Model Development:

- Construct a decision model that represents the relationships between criteria and potential renewable energy locations.
- Implement the selected MCDM method(s) to calculate the overall performance or suitability of each location based on the normalized criteria values.
- Generate the rankings or scores for each potential location using the MCDM method(s).

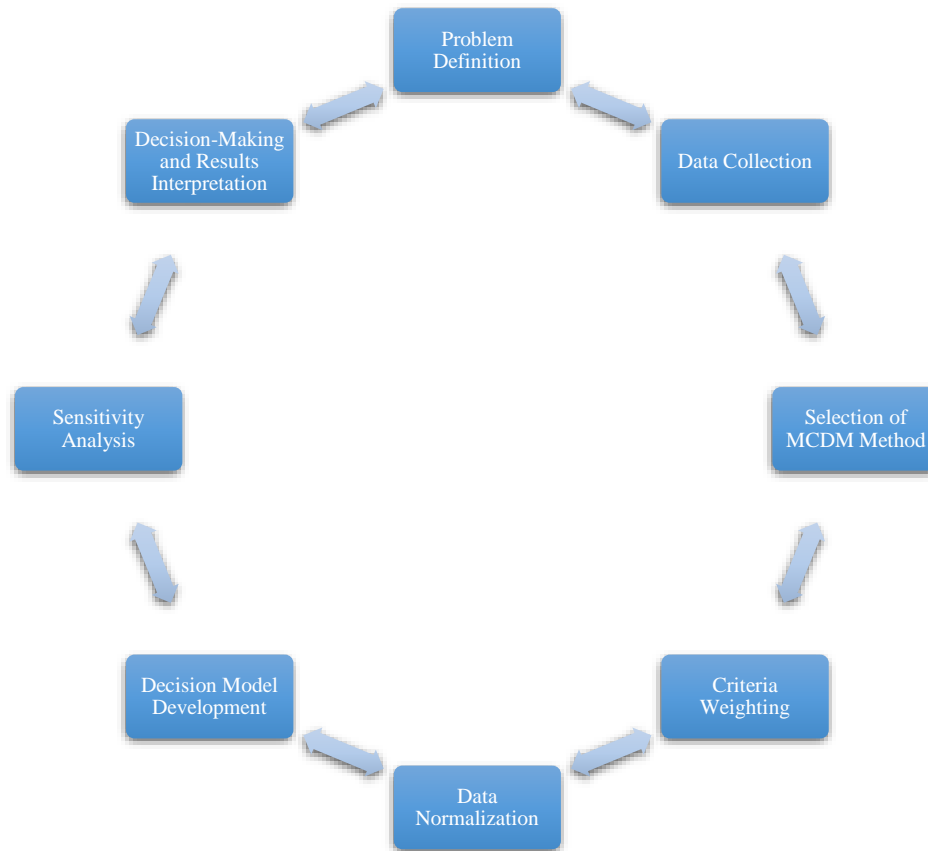
7. Sensitivity Analysis:

- Conduct sensitivity analysis to examine the robustness of the decision model and the influence of criteria weights on the final results.
- Investigate the changes in rankings or scores when criteria weights are adjusted within certain ranges.
- Evaluate the stability and consistency of the decision model under different scenarios.

8. Decision-Making and Results Interpretation:

- Interpret the results obtained from the MCDM method(s) to determine the optimal renewable energy locations in disruption situations.

- Consider the rankings, scores, and sensitivity analysis to make informed decisions.
- Communicate the results effectively to stakeholders, policymakers, and investors, highlighting the rationale behind the chosen locations and the potential benefits [31-32].



**Figure 2:** MCDM Method.

#### 4. Results and discussion

This section would present the specific data collected for each battery type and criteria, the normalization calculations, and the ranking obtained using the chosen MCDM method. You can use tables, graphs, and visualizations to effectively present the results.

The numerical results section presents the outcomes of the MCDM analysis conducted on lithium-ion battery types. The criteria weights, as determined through expert opinions or data-driven approaches, are applied to rank and prioritize the chosen battery.

The results show suitable decision on lithium-ion battery types by MCDM approach. The matrix of decision making for selecting lithium-ion battery that is determined by experts is as follow (Table 2-4 and Figure 3):

**Table 2:** Lithium-ion battery types.

Lithium-ion battery types	Energy density	Power density	Cycle life	Safety	Cost	Environmental impact
Weight	0.10	0.20	0.10	0.20	0.20	0.20
NMC	87%	95%	92%	87%	1	100%
LiFePO4	90%	97%	98%	92%	1.5	92%
LCO	98%	95%	86%	86%	2	95%
LMO	96%	90%	96%	96%	2.5	99%
Li4Ti5O12	85%	100%	86%	90%	3	88%

In the numerical results section, the study presents the outcomes derived by utilizing the MCDM method for the selection of lithium-ion battery. The findings are based on the evaluation and weighting of criteria, taking into account specific preferences and constraints related to the context. The MCDM results will be demonstrated through rankings, scores, or decision matrices, highlighting the relative performance of various lithium-ion battery alternatives. The analysis will focus on both the merits and constraints of the selected MCDM technique(s), and how they were applied in the process of selecting renewable energy sources.

**Table 3:** Type of criteria.

Lithium-ion battery types	Energy density	Power density	Cycle life	Safety	Cost	Environmental impact
Weight	0.10	0.20	0.10	0.20	0.20	0.20
Type	1	1	1	1	-1	-1
NMC	87%	95%	92%	87%	100%	100%
LiFePO4	90%	97%	98%	92%	150%	92%
LCO	98%	95%	86%	86%	200%	95%
LMO	96%	90%	96%	96%	250%	99%
Li4Ti5O12	85%	100%	86%	90%	300%	88%

**Table 3:** Python code for assessing lithium-ion battery types by MCDM

```
import numpy as np
from pymcdm.methods import TOPSIS, VIKOR, COPRAS , PROMETHEE_II, COMET, SPOTIS, ARAS,
    COCOSO, CODAS, EDAS, MABAC, MAIRCA, MARCOS, OCRA, MOORA

from pymcdm.helpers import rrankdata
```

```
# Define decision matrix (2 criteria, 4 alternative)
alts = np.array([
    [0.87,0.95,0.92,0.87,1,1],
    [0.9,0.97,0.98,0.92,1.5,0.92],
    [0.98,0.95,0.86,0.86,2,0.95],
    [0.96,0.9,0.96,0.96,2.5,0.99],
    [0.85,1,0.86,0.9,3,0.88]
], dtype='float')
# print (alts)

# Define weights and types
weights = np.array([0.1,0.2,0.1,0.2,0.2,0.2])
types = np.array([1,1,1,1,-1,-1])

# Create object of the method
topsis = TOPSIS()
# Determine preferences and ranking for alternatives
kkk1= topsis(alts, weights, types)
print ("topsis",kkk1)

# Create object of the method
vikor = VIKOR()
# Determine preferences and ranking for alternatives

kkk=vikor(alts, weights, types)

print ("vikor",kkk)

# Create object of the method
copras = COPRAS()
# Determine preferences and ranking for alternatives
kkk=copras(alts, weights, types)
print ("copras",kkk)

# Create object of the method
moora = MOORA()
# Determine preferences and ranking for alternatives
kkk=moora(alts, weights, types)
print ("moora",kkk)

# Create object of the method
mabac = MABAC()
# Determine preferences and ranking for alternatives
kkk=mabac(alts, weights, types)
print ("mabac",kkk)
```

**Table 4:** Results of assessing lithium-ion battery types by MCDM

Lithium-ion battery types	TOPSIS	VIKOR	COPRAS	MOORA	MABAC	Total
NMC	0.43	1.00	1.00	0.13	-0.04	0.50
LiFePO4	0.67	0.00	0.98	0.12	0.25	0.41
LCO	0.40	1.00	0.90	0.09	-0.04	0.47

Lithium-ion battery types	TOPSIS	VIKOR	COPRAS	MOORA	MABAC	Total
LMO	0.43	0.91	0.87	0.07	0.01	0.46
Li4Ti5O12	0.52	0.84	0.84	0.06	0.05	0.46

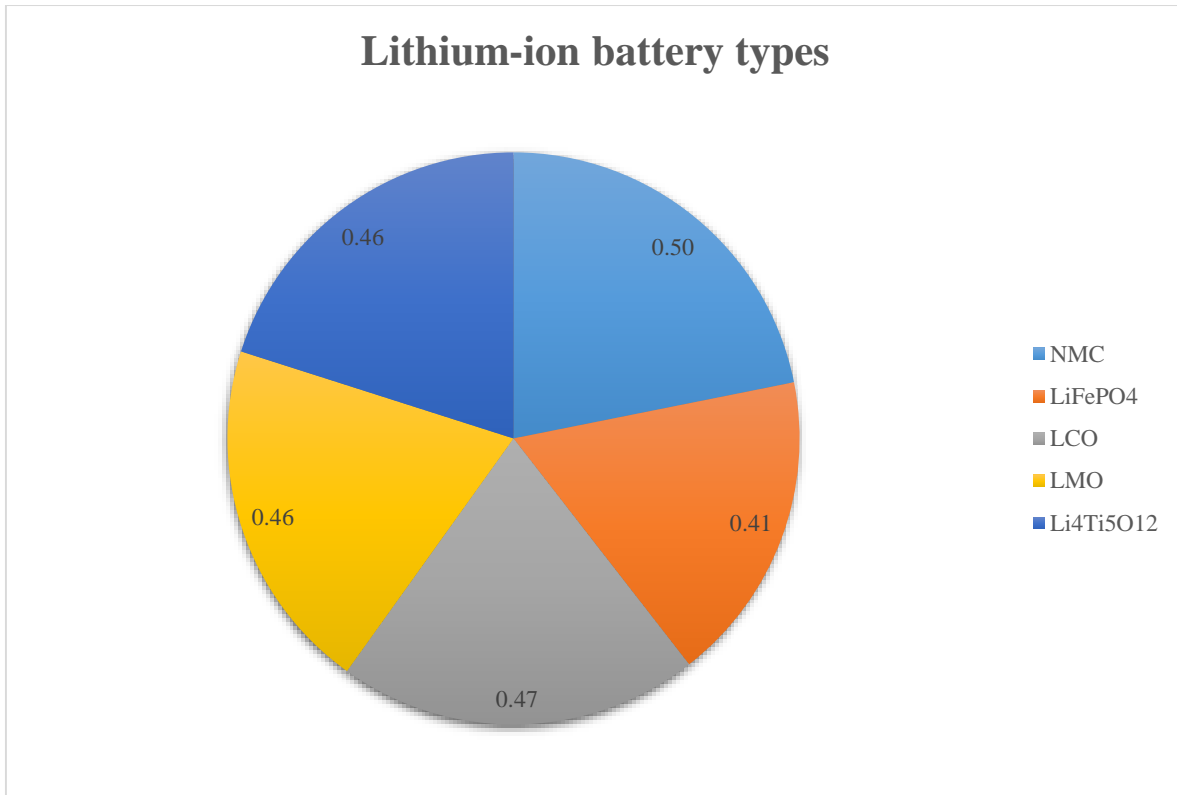


Figure 3: Results of MCDM method.

Lithium-ion battery types:

This column lists different types of lithium-ion batteries being evaluated, such as NMC, LiFePO4, LCO, LMO, and Li4Ti5O12.

TOPSIS:

This column represents scores or rankings assigned to each lithium-ion battery type based on the TOPSIS (Technique for Order of Preference by Similarity to Ideal Solution) method.

For example, NMC has a TOPSIS score of 0.43, LiFePO4 has a score of 0.67, LCO has 0.40, LMO has 0.43, and Li4Ti5O12 has 0.52.

#### VIKOR:

This column shows the scores or rankings assigned by the VIKOR (VlseKriterijumska Optimizacija I Kompromisno Resenje) method.

NMC and LCO both score 1.00, indicating they are considered the best according to the criteria used in this method. LiFePO<sub>4</sub> scores 0.00, suggesting it might not perform as well based on these criteria in the VIKOR method.

#### COPRAS:

This column presents the scores or rankings given by the COPRAS (COMplex PROportional ASsessment) method.

NMC, LiFePO<sub>4</sub>, LCO, LMO, and Li<sub>4</sub>Ti<sub>5</sub>O<sub>12</sub> have scores of 1.00, 0.98, 0.90, 0.87, and 0.84, respectively. These scores reflect their performance according to the criteria used in the COPRAS method.

#### MOORA:

This column displays scores or rankings from the MOORA (Multi-Objective Optimization by Ratio Analysis) method.

NMC has a score of 0.13, LiFePO<sub>4</sub> scores 0.12, LCO has 0.09, LMO has 0.07, and Li<sub>4</sub>Ti<sub>5</sub>O<sub>12</sub> has 0.06. These scores represent how well these battery types perform based on the criteria assessed by MOORA.

#### MABAC:

This column represents the scores or rankings given by the MABAC (Multi-Attributive Border Approximation Area Comparison) method.

NMC has a score of -0.04, LiFePO<sub>4</sub> scores 0.25, LCO has -0.04, LMO scores 0.01, and Li<sub>4</sub>Ti<sub>5</sub>O<sub>12</sub> scores 0.05. These scores indicate the performance or preference of each type according to the criteria used in MABAC.

Total:

This column might represent an overall or aggregated score across all the methods or a calculated total based on certain criteria.

For instance, it seems to be a combined score calculated from the individual scores in each method. The values for each battery type range from 0.41 to 0.50, summarizing their performance across the different evaluation methods.

These scores or rankings are specific to the criteria used within each method and are meant to assess and rank the performance or preference of different lithium-ion battery types based on those criteria.

## **5. Conclusion**

The assessment of lithium-ion battery types through MCDM methods provides valuable insights into their performance across various evaluation criteria.

Analyzing the table, it's evident that different methods yield diverse rankings and scores for the evaluated battery types. This variation underscores the sensitivity of the assessment to the specific criteria and methodology employed in each decision-making technique.

The TOPSIS method tends to favor LiFePO<sub>4</sub>, assigning it the highest score among the evaluated types. Contrastingly, VIKOR positions NMC and LCO at the top, indicating their superiority based on its criteria. COPRAS also favors NMC, LiFePO<sub>4</sub>, and LCO, though their respective rankings differ slightly from VIKOR.

MOORA's assessment portrays varying preferences, emphasizing different types' strengths compared to other methods. Meanwhile, MABAC introduces another perspective, highlighting LiFePO<sub>4</sub> as a strong contender, while NMC and LCO have relatively lower rankings in its evaluation.

The collective assessment from these methods presents a complex landscape where different lithium-ion battery types demonstrate strengths and weaknesses depending on the specific criteria considered.

Overall, the evaluation underlines the importance of considering multiple decision-making methods to comprehensively assess lithium-ion battery types. It emphasizes that no single battery type uniformly excels across all criteria, suggesting the significance of defining priorities based on specific application requirements when selecting the most suitable lithium-ion battery type. Additionally, the discrepancies in rankings across methods emphasize the necessity of a nuanced approach in decision-making, accounting for diverse perspectives to make informed and context-specific choices in battery selection for various applications.

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