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A decision support tool for multi-attribute evaluation of demand-side commercial battery storage products

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Abstract

With the diversification of commercial energy storage technologies, choosing a suitable technology is becoming a complex decision-making process. The complexity is rooted in the many decision criteria such as technology, brand reputation, energy capacity, volume, weight, aging, and warranty among many others. As such, for non-expert users, particularly small households or enterprises, the act of energy storage adoption is becoming growingly cumbersome. To address this problem, this paper introduces a decision support tool for the evaluation of commercial (small-scale) energy storage products. It then identifies the most suitable option(s) based on the users' preferences.

For the reasons elaborated in the paper, nine multi-criteria decision-making (MCDM) methodologies have been employed. Altogether, 19 attributes are identified for the evaluation of (battery) energy storage technologies. The decision support tool is developed in the Matlab environment and includes a graphical user interface for easier interaction of non-expert users. For the demonstration, three scenario cases have been studied for users with different preferences. The ranking results clearly show the marked impact of users preferences on the recommended energy storage technologies. This implies that a tool like this can help small users in the selection of their right technology and avoid resource loss due to inappropriate technology selection, which can be neither economical nor sustainable.

Keywords: Energy storage; battery; multi-attribute decision-making; multi-criteria; technology screening.

1 Introduction

1.1 Energy storage technologies

Renewable energies have made an undeniable revolution over the recent decade and technologies such as solar photovoltaics (PV) and wind have developed rapidly growing supply chains from manufacturing to end-users [1]. According to the initial observations, lower investment costs are the reason why fossil fuel generators have become the main energy source. However, in terms of LCOE, traditional fossil fuels can no longer compete with energy generated from renewable resources [2]. Renewable energies have several advantages particularly rooted in their diverse natural sources such as sunlight, wind, rain, and tide. They are also available almost all over the world and in contrast to fossil fuels, no place on earth can be found without access to at least one source of renewable energy. These advantages have converted renewable energy a focal point in the social and energy context.

There is an increasing number of manufacturers who provide renewable energy technologies with diverse features for users from households to industrial complexes. The key limitation of renewable energies, unlike fossil fuels, is their variability which creates a mismatch between supply and demand. This necessitates the consideration of energy storage systems. It is relatively easy to store fossil fuels due to their solid or fluid forms. Nevertheless, it is a big challenge for renewable energy sources, such as solar and wind electricity. From another perspective, for the electricity network, energy storage plays a significant role in the reliability of the whole grid system, by helping to balance the power supply and demand [3].

While in the past energy storage has been mainly considered for large scale applications [4], it is becoming equally important for the end-user households or commercials. In many jurisdictions, to motivate end-user investment in renewable energy technologies, the feed-in tariff (FIT) has been equal to or even higher than the cost of grid electricity. The so-called prosumers can export their surplus energy to the grid and receive an attractive FIT. However, this trend is gradually changing and over time the FIT is declining to values lower than grid electricity [5]. For instance, while the retail electricity price was less than 20 c/kWh in Sydney, Australia, in 2010, the FIT was 60 c/kWh. Since then, despite the increase in retail electricity price, the FIT has declined to values of less than 10 c/kWh [6]. Hence, the grid becomes no longer an attractive energy buffer for the prosumers and motivates them in finding opportunities to store their surplus electricity for later use rather than selling at low FIT values. This has created an increasing interest in demand-side energy storage devices, especially battery technologies. In this line, also, some markets are being created where electricity retailers offer various packages of electricity tariff, renewable energy technology, and battery storage. It is from this point that the key motivation of this study was initiated. There are diverse ways of storing energy including electrical, mechanical, chemical, and thermal [7]. Chemical energy storage can be further subdivided into thermal energy storage, chemical energy storage and thermochemical energy storage (See Figure 1).

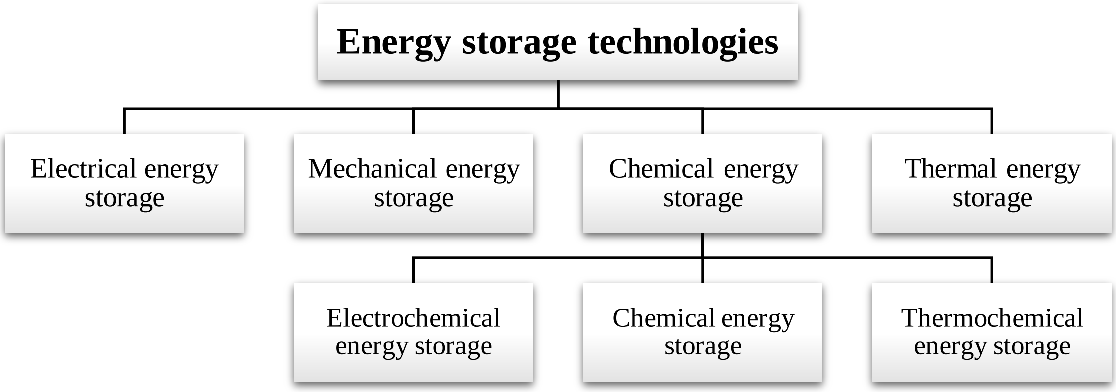


Figure 1: Some classification of energy storage technologies

Among them, the battery is the most traditional form of energy storage, with fuel flexibility, environmental benefits and other advantages [8]. But, even for batteries, there are many manufacturers with diverse technologies and attributes. Akindele & Rayudu [9] have identified the following attributes: technology power rating, discharge time, discharge losses (day), suitable storage duration, cycling capacity, Lifetime (years), energy and power density, and round-trip efficiency (%). Hence, a new decision-making problem has emerged which is around the selection of the right energy storage options from a variety of choices. This requires the employment of multi-attribute decision-making tools. While for large-scale industries, it is feasible to utilise the help of a consulting company in decision-making, for small-scale households or commercials this is a cumbersome task. The objective of this paper is to introduce a decision support tool to help small-scale prosumers in making the right decision.

1.2 Evaluation methodologies

Multi-Criteria Decision Making, Multi-Criteria Decision Analysis or Multi-Attribute Decision Making (MCDM, MCDA, or MADM)[1] is a sub-discipline of operations research. It aims at structuring complex decision-making problems into simple, comprehensive, and operable forms for the decision-maker [10]. The evaluation process is based on attribute comparisons involving trade-offs between the attributes [11]. It can handle incommensurable objectives

[1] In the literature, as well as in this paper, the terms MCDM,MCDA and MADM are used interchangeably.

such as cost, profit, efficiency, and safety and as such, it is finding widespread applications particularly in addressing complex sustainability issues [12]. The MCDM structure is composed of four elements: 1) criteria and attributes, 2) alternatives, 3) weights, and 4) performance data. In the context of this paper, MCDM is an approach that combines decision criteria, battery product information, and decision-maker preferences to evaluate the alternatives to select the most preferred one. When the decision-makers are engaged with this kind of problem, the essential factor which differentiates the alternatives are the decision maker’s preferences [11].

Interest in the MADM method has increased rapidly, and there is a broad range of applications in many fields, such as the environment, energy, engineering, construction, and automobile manufacturing industries [11]. Mardani et al. [13] reviewed 393 articles on academic databases of Web of Science published from 2000 to 2014. They classified the articles into 15 groups based on the application area. Of these, 53 papers (13.4% of the total publications) were in the field of energy, environmental and sustainability, being the second-highest field. The study found that the most used tool and approach was the AHP method (32.6%). The second place was a hybrid MCDM (16.3%). Aggregation DM methods (11.7%), TOPSIS (11.4%), and ANP (7.4%) were listed at the 3rd to 5th place in the ranking [10]. Behzadian et al. [14] reviewed 266 scholarly papers from different databases and categorised papers into nine application areas. They found that though the TOPSIS had been applied to a wide range of application areas, it still broadly focused on social decision problems as the main application area. Govindan et al. [15] reviewed the application of MCDM techniques in green supplier evaluation and selection problems. They found that AHP was the most widely used MCDM technique. Pohekar and Ramachandran [16] pointed out that in the context of sustainable energy planning, AHP is the most widely-used method, accounting for around 20% of papers. Kumar et al. [17] discussed that AHP, ELECTRE III and PROMETHEE are popular methods in the literature due to their procedural simplicity. However, it is difficult to identify one single MCDM method as the best one as each method has its own pros and cons. This has given rise to suggesting hybrid techniques [18]. Shahnazari et al. [19] concluded that the Plasma method is the best thermochemical technique, by using a combination of the AHP and TOPSIS methods. Lin et al. [20] claimed that the advantage of the combined methods is flexibility. They can be adopted into many kinds of requirements of projects. Hybrid methods have also some opponents claiming that hybridisation brings along reduced transparency of the method and users may not really understand the process correctly.

We have divided MCDM techniques into three categories (See Figure 1). In the first category, criteria weights and attribute data of the alternative items are the basis of the preference model. Analytical hierarchy process (AHP) Sum Average Weighted (SAW), Analytic Network Process (ANP), Weighted Product Model (WPM), Simple Multi-Attribute Rating (SMART), are belonging to this category. The second category is creating preference selection between the alternatives, such as Elimination and Choice Expressing Reality (ELECTRE), Preference Ranking Organization Method for Enrichment of Evaluations (PROMETHEE) [21]. The third category includes programming methods, such as GP, GRA, and some combination methods. Goal programming is a method also used in the wider area of multi-objective optimization which studies models with continuous decision variables. We do not consider other methods considered in that area.

Table 1: Some MCDM methods studied in this work

	MCDM models	
	Short name	**Full name**
Category 1 (models with criteria weights)	AHP	Analytical Hierarchy Process
	ANP	Analytical Network Process
	WSM & WPM	Weighted Sum Model & Weighted Product Model
	SAW	Simple Additive Weighting
	SMART	Simple Multi-Attribute Rating Technique
Category 2 (models with preference selection between alternatives)	PROMETHEE	The Preference Ranking Organisation Method for Enrichment Evaluation
	TOPSIS	Technique for Order of Preference by Similarity to Ideal Solution
	CODAS	Combinative Distance-based Assessment
	VIKOR	Vlsekriterijumska optimizacija i KOmpromisno Resenje
	MABAC	Multi-attributive Border Approximation Area Comparison
	COPRAS	Complex Proportional Assessment
Category 3 (models with programming or methods combination)	GRA	Grey Relational Analysis
	GP	Goal Programming
	AHP-TOPSIS	Analytical Hierarchy Process + Technique for Order of Preference by Similarity to Ideal Solution
	AHP-GP	Analytical Hierarchy Process + Goal Programming

The purpose of this study is to use MCDM methodologies to select the most suitable electricity energy storage technology (EST) with a particular focus on the battery for home or small business applications. The diversity of energy storage technology attributes is the reason for using MCDM for evaluation. It is a complex decision with multi-criteria comparisons, such as performance criteria, physical criteria, or life-cycle cost. Before the evaluation of the EST devices, MCDM methods should be chosen through an efficient assessment procedure. For this, different MCDM algorithms, and result comparisons were implemented. All of the above-mentioned MCDM methodologies (See Table 1) can be used for addressing this problem. A detailed review of this topic has been provided by Baumann et al. [22]. Each method has its advantages and disadvantages. Therefore, there are two possible pathways in choosing the right method for a given application (e.g., energy storage here). One is to evaluate and compare two or more methods in parallel. The alternative is to combine different MCDM methods utilising complementary advantages of each one and build a hybrid tool that can work more efficiently than any single method. Therefore, the MCDM for EST research is founded on three key questions:

- What features of EST devices need to be considered?
- Which MCDM methods are appropriate for the evaluation of the EST device?
- Which EST is the best solution for a given customer?

These questions will be discussed in the remaining sections. The model development procedure as well as the structure of this paper is presented in Figure 2. The first step is the identification of the most suitable MCDM method [23]. Then comes the decision criteria identification, which leads to the data collection phase.

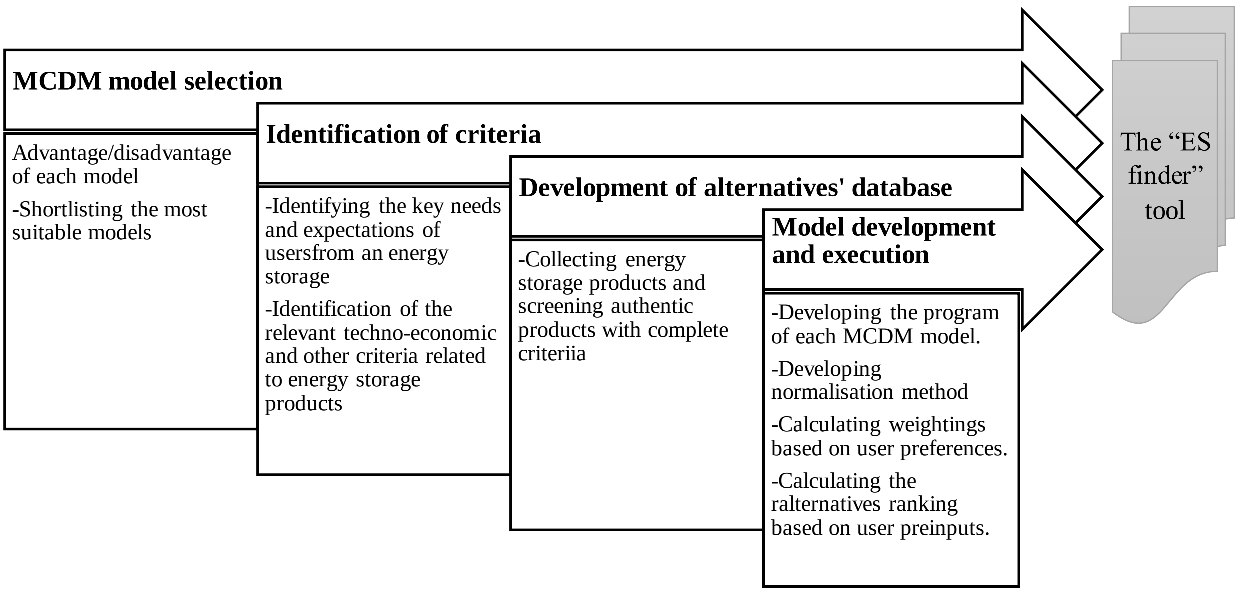


Figure 2: The MCDM process development procedure for energy storage selection tool

With these, the final stage would be program development and execution. Each of these steps is discussed in the following sections, with the method selection coming first.

2 Evaluation of the MCDM methods

2.1 Review of some MCDM models

AHP: The Analytic Hierarchical Process (AHP) is one of the broadly used MCDM techniques proposed by Saaty in 1980 [24]. An architectural hierarchy means to break down problems in a complex system into components. AHP is based on constructing the hierarchical elements such as goals, criteria, weights, and choices of complex problems, and then pairwise comparing all features systematically (See Figure 2) [25].

Asadabadi et al. [26] have suggested modifying the scale from 1 to 9. It is firstly proposed by Saaty [27]. The size of the number is proportional to the degree of importance. The last step is to compute the final score for each option by ranking weighted alternatives [28]. There is a possibility that each different attribute will be arranged at a different level. Decision-makers need to use their knowledge and experience for pairwise comparison of collections at each level. This can, however, cause some degree of inconsistency between personal decisions and subjective judgments. To solve this problem, AHP uses the calculated consistency ratio, known as consistency verification, which is one of the greatest strengths of AHP [29]. The structure of the hierarchy will be shown in Figure 3.

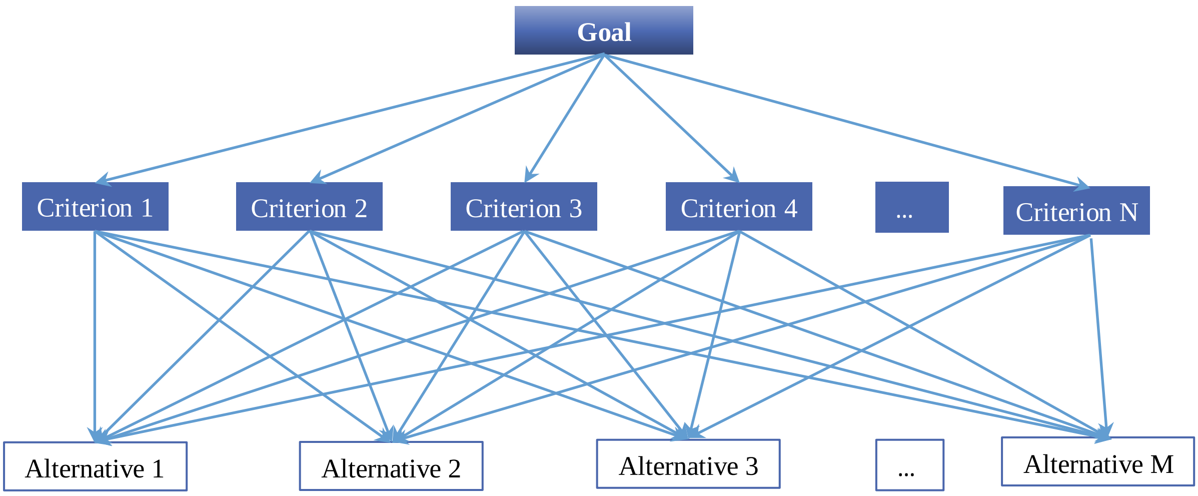


Figure 3: AHP model structure

As the experience of using AHP has increased, three main weaknesses of AHP have been discovered. Firstly, after cases studied by Triantaphyllou [30], irregularity of ranking cannot be avoided in the process of the AHP. However, Salo and Hämäläinen [31] have shown that with a change in the way of questioning in the preference elicitation, this problem can be avoided. The second weakness of AHP is time-intensiveness. Finally, the interrelation between each choice is not found in the process of AHP, while it is possible with the ANP.

ANP: This was proposed by Saaty [32] to address the weakness of the AHP regarding the associations within breakdown elements. Compared with the AHP, which needs to assume the independence of elements, both at different levels and the same level, ANP only needs to set up a network framework instead of specifying the level. However, ANP is still able to compare each element pairwise. In ANP, the first step is to assume each cluster and element, and then super metrics can be built by the elements. Through Saaty 's scale mentioned in AHP, they will be compared in pairs [27]. The goal is to get a cumulative effect between the elements [26]. ANP still inherits some shortcomings of AHP; for example, it takes a long time to implement all projects again. AHP has the advantage that it is easier than ANP to make sense to a user in a real application. Meanwhile, ANP is more complicated than AHP to implement in software.

TOPSIS: This is a classic and useful technique based on distance measurement developed by Hwang & Yoon [33]. TOPSIS principle is based on selecting a scheme which is closest to the positive-ideal solution, while conversely, it is farthest from the negative ideal solution [34]. With the development of this technology, the amount of disguised development of this technology has been studied, AHP-TOPSIS being one of them.

PROMETHEE: Macharis et al. [35] proposed the PROMETHEE in two formats, one is partial ranking named as PROMETHEE I, and the other is complete ranking named as PROMETHEE II, and it was applied to the field of health care in the same year. PROMETHEE II has over time found more applications. The PROHEMEE method can provide decision-makers with pure decision consciousness through neutrally and strictly evaluating variables [36]. Nevertheless, when establishing the corresponding function with PROMETHEE, there are two shortcomings, which are relying heavily on assumptions and changing the structure of the problem. They come from the simplification of multi-criteria issues. The PROMETHEE method can guarantee the reliability of the information but not the existence of conflicting variables [37].

VIKOR: This method has been reported as a powerful MCDM tool [30-31]. Different from TOPSIS, VIKOR considers the relative importance between the distance calculated. VIKOR method calculates the compromise ranking and produces at least three groups of alternatives calculated based on different requirements to make the ranking. Its popularity derives from its actuarial algorithms and accurate results [40].

GP: Goal programming (GP) is also a popular method, identical to linear programming in the MCDM context. It has been applied in many MCDM problems, such as nurse scheduling [41], quality control systems [18], and project risk management [42].

SAW: As Podvezko [43] stated, SAW is a traditional, practical and direct approach that has the advantage of simple algorithms and the ability to visually compare the differences between alternatives. To find the best alternative through SAW, the solution is to sort and summarise the weight value obtained from the standard level multiplied by the relative weight [44]. At the same time, it holds some disadvantages. The maximisation of the value in the criteria leads to the result that cannot image the truth or even cannot entirely responsive to the logic [45].

SMART: This is one of the most commonly used methods by the MCDM community [46]. It considers the attribute ranges explicitly, and by this makes it easy to apply. It weights attributes in two simple steps by first ranking the importance of the attributes and then estimating the ratio of the prominence of the attributes relative to the least important attribute [47].

WSM & WPM: These two methods are alike and are often used together because WSM is primarily used for one-dimensional problems, while WPM deals with multi-criterion issues [48]. The difference between these two approaches is the algorithm of each approach. WSM uses addition, while WPM uses multiplication [49].

GRA: This was developed by Julong (1989), with many applications in engineering, social science, economics, and many other specialised fields. The advantage of GRA is that it obtains the trend by analysing the data curve, and this trend can be referred to as the scale of the selected variable. The linear analysis makes the decision-making process easy to understand. Moreover, the suitability is related to the two values, which can make the decision-maker more intuitively see the difference between the alternatives [51].

AHP-TOPSIS: The theoretical basis of combining AHP and TOPSIS is to determine the relative importance of the criteria by AHP and measure the distance by TOPSIS to satisfy the selection of determined alternatives. The advantage of TOPSIS is that it is a straightforward process to implement in code, thus making up for the operational difficulties of AHP. However, AHP can complete the process of setting weights missing in TOPSIS. The order of use of this method is first to determine the criteria in the model, then use AHP to grade variables and assign weights, and finally, use TOPSIS to realise code calculation and discover the ideal replacement scheme [52].

AHP-GP: In this method, AHP and GP are combined by incorporating priorities of weight into the target programming model. According to Velasquez and Hester [53], the AHP method is supplied to solve the problem that GP's weakness in weight in alternatives. Meanwhile, what

GP can do for AHP is to provide compensation in terms of target constraints and to prevent inconsistency. Furthermore, it can remedy the weakness of AHP in dealing with large-scale problems [54]. As a hybrid product, this combination also inherits the time-consuming disadvantage of AHP.

CODAS: In this method, two distance calculation approaches are used, Euclidean Distance (ED) and Taxicab Distance (TD), among which Euclidean distance is the initial calculation method. However, when the Euclidean distance calculated by the two alternatives is too close, continue to calculate the two alternatives with the Taxicab distance and find a more appropriate option that improves the accuracy of the selection [55]. To enhance the applicability of CODA method, it has been combined with other methods such as Fuzzy-AHP (FAHP) and CODAS, Interval-Intuitionistic Fuzzy (IVIF) sets and CODAS. Fuzzy CODAS method is applied to the evaluation and decision-making of market segmentation to improve the competitiveness of enterprises [56], renewable energy alternatives [57], and wave energy facility location selection [58]. This shows the adaptability of CODAS as a decision technology in different fields.

MABAC: This is designed to calculate the distance between the alternatives and Border Approximation Area (BAA), while the normalisation can be separated into cost and beneficial criteria [59]. MABAC is a practical method that can give the solution with stability and reliability [60]. The benefits of using BAA are computing stable results from MABAC, easily calculating the equations, accounting the gains and loss of the values, and adaptability of combing with other methods [59]. MABAC or its combinations have been used in a variety of fields, for example, machining processes selection and evaluation [60], university web pages evaluation [61], and resource management in logistics centre [62].

COPRAS: This is one of the latest MCDM technologies. Some of its advantages include ease of understanding, short calculation time, and output can be the total ranking of alternative schemes. The maximum and minimum standards can be calculated separately during COPRAS implementation [63]. When COPRAS calculates the index of Alternatives, it divides the criteria into cost and beneficial types and combines the two index types to calculate the scoring of alternatives. When COPRAS is used in complex data computing processes, accurate answers can be successfully obtained, so its accuracy is guaranteed. The implementation of COPRAS is easy to obtain the best alternatives for decision-makers [64].

2.2 Evaluation of the MCDM methods

As elaborated in the previous section, each MCDM method has its weaknesses and strengths. The behavioural effects of the modeller and the modelling process are also highlighted in the literature [65]. Consequently, the evaluation and selection of the right MCDM technologies is by itself an MCDM problem. For such an evaluation, there have been introduced four attributes including understandability, implementable, time-consumption, and popularity [66]. Table 2 provides a tabulated analysis of the discussed methodologies based on their advantages and disadvantages.

Table 2: Advantages and Disadvantages of Some MCDM Methods (Adapted and modified from [66])

MCDM method	Advantages	Disadvantages
AHP	Hierarchy structure; ratio scale; pairwise comparison; easy to use; scalable; well-known	Ranking irregularities; time-consuming; possibility to revise; inability to reflect huge importance
ANP	General; independent relationship;	Complex; hard to implement
TOPSIS	Simple; easy to use; ability to remains the same number of processing steps no matter how many attributes	Neglect of correlation between the criteria; best option might be close to the ideal point and nadir point; difficult to weight criteria; difficult to keep the consistency of judgment
PROMETHEE	Simplification of human perceptions and judgments; ease to deal with incomparable important criteria	No real decision problem structure; ambiguous weighting assignment; heavily rely on decision-makers; possibility to revise; complex
SAW& SMART	Ability to compensate among criteria; easy to use; simple implementation	Inability to always reflect the real situation; yielded alternative might not be the right one..
WSM&WPM	Simple; well-known; ability to multi-dimensional problems	Additive utility assumption: inability to apply to multi-dimensional problems; sensitive to the scope of the unit; possibility to exaggerates some scores
GP	Ability to handle large-scale problems; Ability to produce infinite alternatives.	Yielded alternative might not Pareto efficient; inability to weight coefficient
CODAS	Easy to understand; double calculation for distance ensures the accuracy	No real decision problem structure; ambiguous weighting assignment; neglect of correlation between the criteria;
MABAC	Easy to calculate; stable ranking results; tolerance of data loss;	No real decision problem structure; ambiguous weighting assignment;

	adaptability of combing with other methods	neglect of correlation between the criteria;
COPRAS	Newest method; stable ranking results; calculation for separated attributes; Complex data processing capabilities	No real decision problem structure; ambiguous weighting assignment; neglect of correlation between the criteria;

We also use the four evaluation attributes for a quantitative comparison of the methods. Each attribute has a different way to describe the levels. We use the AHP scale for this purpose [11][27]. The scores are:

- Understandability: Hard (1) to Easy (5)
- Implementability: Hard (1) to Easy (5)
- Popularity: Low (1) to High (5)
- Computational time: Significant (1) to Trivial (5)

The weight of these four criteria will be the same, and the final score is the average of the score This leads to the final scoring of the fourteen algorithms presented in Table 3. The best methods have a score of 4.5 (e.g., TOPSIS and VIKOR) Thehybrids of AHP with TOPSIS and GP get the lowest score of 1.5.. Form the result, we have selected those methods which have scores above 3.5. These include AHP, TOPSIS, PROMETHEE, VIKOR, SAW, WSM&WPM, CODAS, MABAC, and COPRAS. The mathematical formulations of the algorithms related to these methods are provided in the Supplementary file.

Table 3: Summary of MCDM methods evaluation and the final score

MCDM Methods	Understandable	Implementable	Time-consuming	Popularity	Average scores
AHP	5	3	1	5	3.5
ANP	3	1	1	3	2
TOPSIS	5	3	5	5	4.5
GP	3	3	3	1	2.5
PROMETHEE	5	1	5	3	3.5
VIKOR	5	3	5	5	4.5
SAW	5	5	5	1	4
WSM&WPM	5	5	5	1	4
AHP+TOPSIS	1	1	1	3	1.5

AHP+GP	1	1	1	3	1.5
CODAS	5	3	3	3	3.5
MABAC	5	3	3	3	3.5
COPRAS	5	3	3	3	3.5

3 Data collection and definition of attributes

3.1 Identification of battery attributes

There exists a variety of possible attributes in the energy storage selection whether being derived from the users' circumstances (e.g., grid connection, indoor or outdoor placement) or the design of energy storage technologies. The identification of a product's attributes can be grounded on factors such as necessity, independence, availability, decomposability, and replaceability. On this basis, Figure 4 has listed six criteria categories including performance, life, physical specifications, function, cost, and general. These categories altogether include a total of 22 attributes that will be used in the selection of the batteries.

The actual capacity of battery products is often different from the ideal size, and the exact capacity is affected by many external factors. Therefore, the nominal capacity of the battery should only be used as a reference, and the reliable capacity should be one of the criteria. Regarding the battery life, the length of the warranty period is one of the attributes, along with cycle life and depth of charge. The physical specification part is to satisfy customers' locational needs. Some users may be needing or willing to place the battery indoors while some others may require outdoor placement. Another issue is the size of the battery (depth, width, height) which again might be a constraint for a user, particularly those living in small apartment or office buildings. Given that usually, there are various sizes and shapes for the same product, the consideration of such products as separate alternatives can create multiple choices leading to a final choice satisfying all the user's constraints. The function feature increasingly becomes important with the higher uptake of renewable technologies. A customer, located off-grid, may require a simple stand-alone battery. While for a grid-connected user inverter is required to make AC/DC conversion and inversion possible. If the product has an inverter, it can save extra money for purchasing one, or a grid connection can guarantee the supply in case of errors occurred. Security is also an important criterion in selecting EST techniques and one attribute representing this is the power-off protection. Battery safety (i.e., different chemistries) is also considered as an attribute under the general category. Beauty is a key factor in product selection which is not much related to the product function. We use the aesthetics feature to reflect this aspect of user decision-making. Often, the cost is one of the most critical attributes for the customer, and this cost includes both ownership and operational costs which are placed under the cost category.

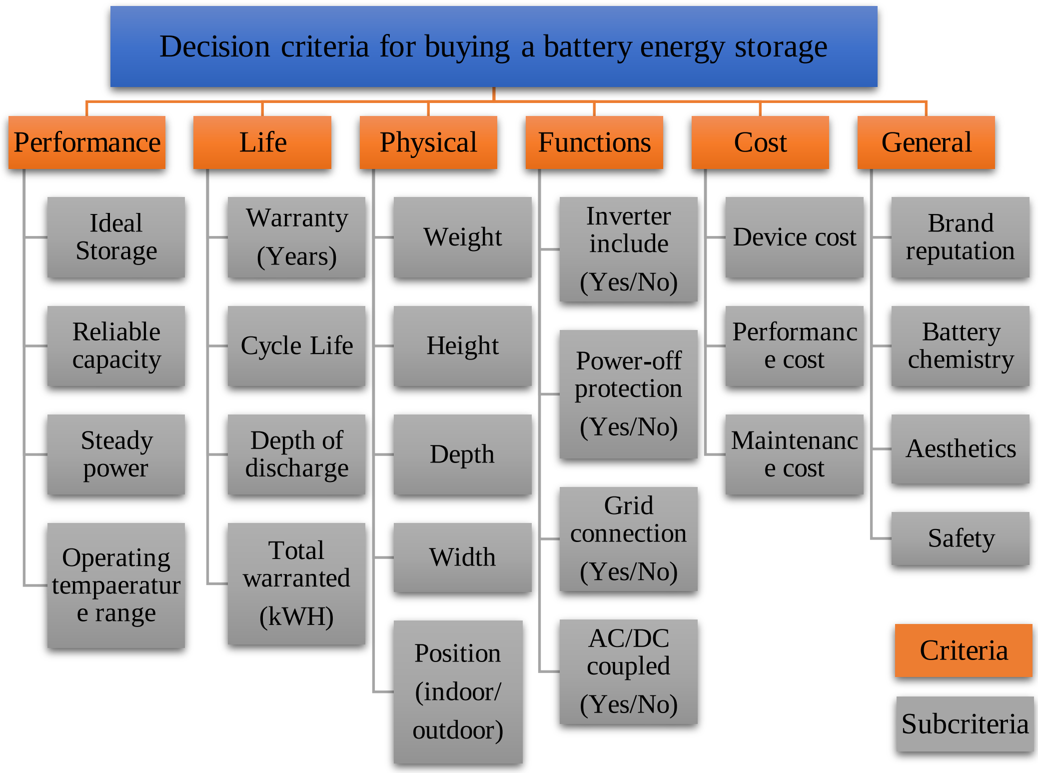


Figure 4: The identified attributes of energy storage technologies for multi-criteria analysis

3.2 Data collection

As discussed before (Section 1.2), alternatives are one of the four key components of an MCDM framework [67]. The data collection should be on a fair and unbiased basis. As discussed by Hämäläinen [65], modelling is a behaviour that may produce cognitive differences, interest motives, and social prejudices. To reduce the burden of stakeholders in the data collection process, thereby affecting the generated in the modelling process, the product details and data collection process avoid direct contact with product distributors, and the data is obtained from third-party websites and the official website of the product. In this line, the data collection for this study is based on the product's certified datasheets on third-party websites and the official website.

There is a growing number of commercial energy storage products. Therefore, the establishment of an integrated database is an essential stage of this MCDM activity. The first step in database development is product screening. There can be problems with the comprehensiveness of the product information provided. For the purpose of this study, if a product datasheet does not have data for all the attributes (see Figure 3), then that product won't be added to the database. The factor is the reliability and timeline of product information. If we are doubtful about the authenticity of the manufacturer or we cannot ascertain the data of the provided information, the given alternative won't be added to the database. The region of sales and the possibility of postage to the user's destination is also another factor that can be considered in database development for a certain customer segment. For instance, for this study, we checked to ensure that the products are available for Australian markets and the prices are indicative of local market values.

4 Implementation – model setup

For the programming environment, we have used Matlab 2020b (Mathworks, USA) and the MCDM resources from Irik [68]. Matlab enables integrated model development connected with graphical user interface (GUI). The method is described in detail in the Supplementary file. The implementation steps are discussed next.

4.1 Qualitative and quantitative criteria

Given that MCDM is a quantitative exercise, the attributes have to be quantitative. Nevertheless, often there will be some qualitative attributes (e.g. options) that need to be converted into quantitative values. But, some criteria are options, so they are assigned to numerical data based on the merits of the options. For the energy storage problem, the type of attributes is provided in Table 4. In the table, the volume criterion reflects the product of three criteria (length, width and height).

Another issue about the attributes is that some of them are favourable (e.g. longer warranty period) while some others are unfavourable (e.g., higher cost). Therefore, the attributes from a favourability perspective, are categorised into two types of cost and benefit. The cost criteria mean that a smaller number has priority, while a larger number in benefit criteria has priority. The cost attributes are set as -1, and the benefit attributes are set as 1 as shown in the last column of Table 4.

Table 4: Classification of energy storage attributes based on the qualitative and qualitative data type and favourability.

Attributes	**Quantitative/qualitative**	**Favourability**
Device price ($)	Quantitative attributes	-1
Warranty (kWh)		1
Warranty (years)		1
Height (m)		-1

Length(m)		-1
Width(m)		-1
Weight (kg)		-1
Nominal capacity (kWh)		1
Usable storage capacity (kWh)		1
Round-trip efficiency (%)		1
Steady power (kW)		1
Peak power (kW)		1
Operating temperature (Min)		-1
Operating temperature (Max)		1
Indoor/ Outdoor	Qualitative attributes	1
All in one (Yes/No)		1
Phase		1
Colours select		1
Product chemistry		1

4.2 Data analysis and processing

The data processing of the optional type needs to be assigned according to the degree of the advantages and disadvantages of the options. According to the analysis of criteria, position, phase, all in one, colour selection and chemical are option data. The position type can be divided into three scenarios of indoor (value of 1), outdoor (value of 1) or both (value of 3). The all-in-one criterion has also two scenarios of yes (value of 1) and no (value of 3). Aesthetics is an important criterion, and, in this database, the product assignment is obtained from the number of colour selections. The maximum number of colour selection is 7.

The chemistry of the EST is one of the most imperative criteria for many reasons including cost, safety, and user attitudes. For example, if in recent years, certain battery chemistry has experienced an explosion with a fatality, it may affect the decision of the users despite the very low possibility of such an incident. Compared with lead-acid and REDOX flow batteries, lithium-ion storage is the most cost-effective in most cases [69]. Therefore, the battery with lithium-ion is assigned the highest score of 3.

4.3 Matrix normalisation

Once the values of the attributes are collected, we will have a matrix with rows being alternatives and columns reflecting each criterion. The general approach in MCDM analysis is to normalise the matrix before computation. However, there are concerns about losing some information through normalisation. For instance, according to Pöyhönen et al. [70], the normalization of weights is one of the reasons that can cause the deviation of the attribute weights. This makes attribute weights dependent on the number of attributes being compared at the same time. Therefore, this article utilises five different normalization methods including Max method, Sum method, Vector method, Max-min method, and Dea method (See Table 5). The comparison of the selected results against the five normalisation methods can improve the transparency of our normalized results. In each method, the matrix is normalised twice, first by treating all data equally (V), and second by inverting the unfavourable criteria (iV), so that the results are consistent with the theory of the first [68].

Table 5: Different normalisation techniques used in this study.

Method	**Formulation**
Max	$V_{ij} = \frac{x_{ij}}{x_j^{max}},\ iV_{ij} = \frac{x_{ij}^{max}}{x_{ij}}$
Sum	$V_{ij} = \frac{x_{ij}}{\sum_{i=1}^{m} x_{ij}},\ iV_{ij} = \frac{\frac{1}{x_{ij}}}{\sum_{i=1}^{m}\frac{1}{x_{ij}}}$
Vector	$V_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^{2}}},\ iV_{ij} = \frac{\frac{1}{x_{ij}}}{\sqrt{\sum_{i=1}^{m}\left(\frac{1}{x_{ij}}\right)^{2}}}$
Max-Min	$V_{ij} = \frac{x_{ij} - x_{ij}^{min}}{x_{ij}^{max} - x_{ij}^{min}},\ iV_{ij} = \frac{x_{ij}^{max} - x_{ij}}{x_{ij}^{max} - x_{ij}^{min}}$
Dea	$V_{ij} = 1 - \frac{x_{ij}^{max} - x_{ij}}{\sum_{i=1}^{m}\left(x_{ij}^{max} - x_{ij}\right)},\ iV_{ij} = 1 - \frac{x_{ij} - x_{ij}^{min}}{x_{ij}^{max}}$

4.4 Entropy weight calculation

Entropy weight case is for the scenario in which the users are interested to provide the minimum preference information and let the MCDM algorithm choose the best option for them. As such they get the best options without setting the weight by themselves. This is suitable for users with immature knowledge of the products and their requirements. $[DM]$ is the original decision matrix, which is created from Step 1 in all the methods algorithms. The $[dWeight]$ is the weight of criteria determined by the decision-maker, which can be changed based on different cases, and the V_{ij} is the matrix after the normalization procedure [68]. In a random case, all criteria weights are set to be equal and 1.

Once the normalisation step is conducted and the normalised matrix V_{ij} is obtained, the entropy weight calculation can be calculated in the following three steps.

Step 1. Compute the entropy for criterion j

$$e_i = \frac{1}{lnm} \sum_{j=1}^{m} V_{ij} \ln(V_{ij}) \tag{1}$$

If $V_{ij} = 0$, then set $\ln(V_{ij}) = 0$.

Step 2. Compute the degree of diversification

$$d_i = 1 - e_i \tag{2}$$

Step 3. Compute the entropy weight

$$w_i = \frac{d_i}{\sum_{i=1}^{n} d_i} \tag{3}$$

4.5 Comprehensive evaluation method

Implementation of AHP: Figure 5 shows the attribute and sub-attribute model structure for AHP. Given that the AHP has a hierarchical structure, its criteria matrix has a different form. This energy storage problem has six attributes (Figure 3), which leads to a 6×6 pairwise comparison matrix. In the second level, the criteria of performance, life, function, and general, each have four sub-criteria. The physical specification and cost criteria each have three sub-criteria. This makes a total of 115 comparison cells. Imagining a case-study with 20 alternatives, the entire comparison cell size will be 20^2×115. The problem will be quadratically increased in size as the number of alternatives increase. This is the origin of the computational time challenge for AHP.

Implementation of rest methods: As the following Figure 6 shown, the attribute model structure for all other methodologies (except AHP) has only one level. These include SAW, CODAS, MABAC, TOPSIS, VIKOR, PROMETHEE, COPRAS. Adding up all the cells that need to be compared gives a vector of 19×1.

Once the attributes structure and the list of alternatives are developed, the Matlab code for each method (source here [68]) was developed.

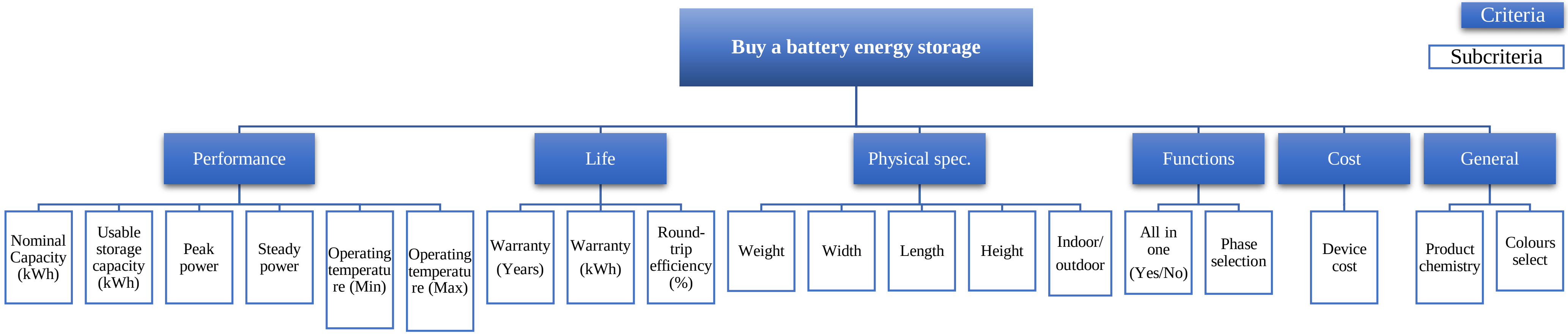


Figure 5: Attribute and sub-attribute model structure for AHP

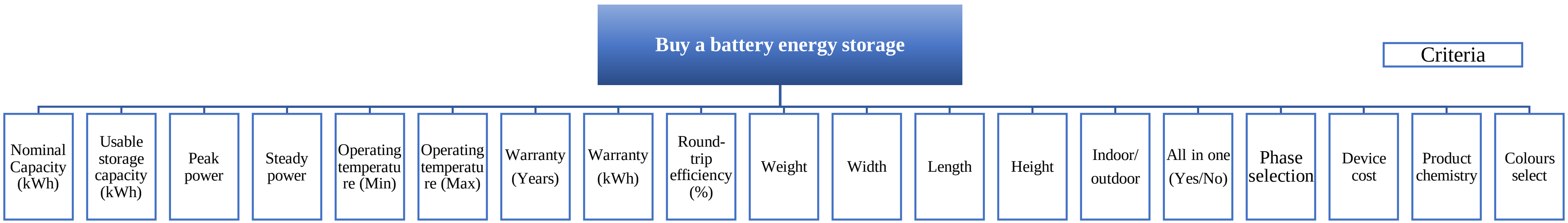


Figure 6: Attribute model structure for all methods used in this study (excluding AHP shown in Figure 4)

4.6 Software tool

The key objective of this study has been to develop a decision support tool for small-scale users such as households or small enterprises. On this basis, not all such users are expected to have expertise in the energy storage or MCDM methodologies. As such, we have developed a user interface to make the product selection experience user-friendly. Figure 6 demonstrates the front page of the ES Finder App. The initial interface of the support tool has three modules. The left column, with drop-down selection, is dedicated to the identification of the six top preferences in the order of concern. Based on the study by Pöyhönen and PHämäläinen [47], in the decision-making process, the original intention of letting decision-makers use numbers is to describe the strength of preference for attributes, however, the results may only express the level of attributes. This will lead to errors in the preference ranking of attributes. In order to reduce the effect of the irregulating by selecting numbers, this tool supply the selection of the attributes with fixed levels and preferences. There are six options of the attributes in the interface, attributes level can be defined by the precedence, attributes preference can be obtained by the times of selection. Once the preferences are selected, the criteria are automatically weighted based on how much the user cares about the attributes. The software also allows the user to choose a certain attribute more than once (to emphasise the importance of that attribute), then the corresponding weight of the attributes is reweighted accordingly. The middle column is related to the selection for the preferred MCDM methods. This is to provide some flexibility to export or semi-expert users who wish to have more control in their decision making. If a user is unsure, they can select the button “All” at the end. Upon clicking any method, the rank of products in the database will be arranged accordingly. Also, when the user wants to know the comprehensive rank relating to all the methods, just click the ALL button. When the “All” option is selected, the software background will calculate all algorithms and comprehensively sort all the options in the database. The right column will show the recommended order, with the first one being the highly recommended product based on user preferences.

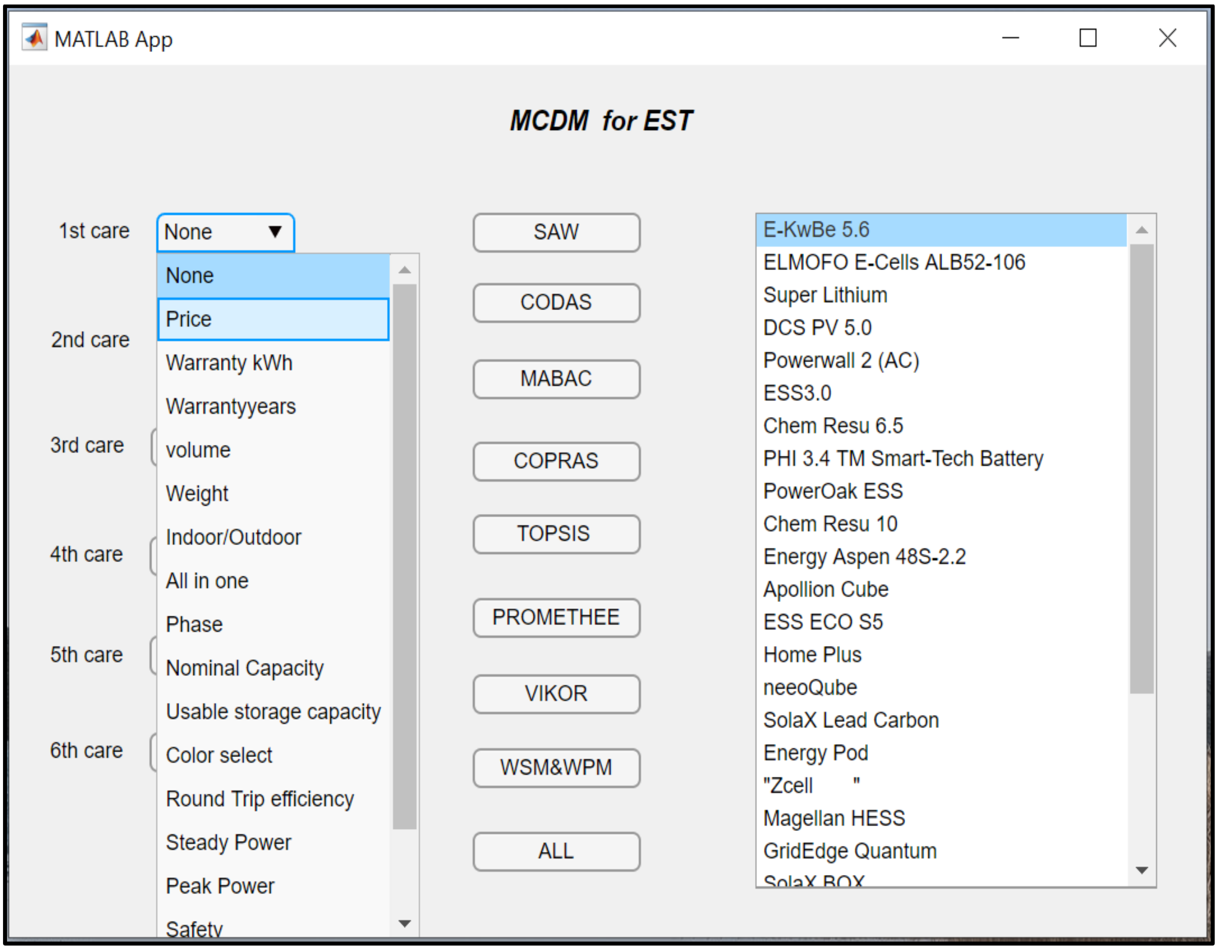


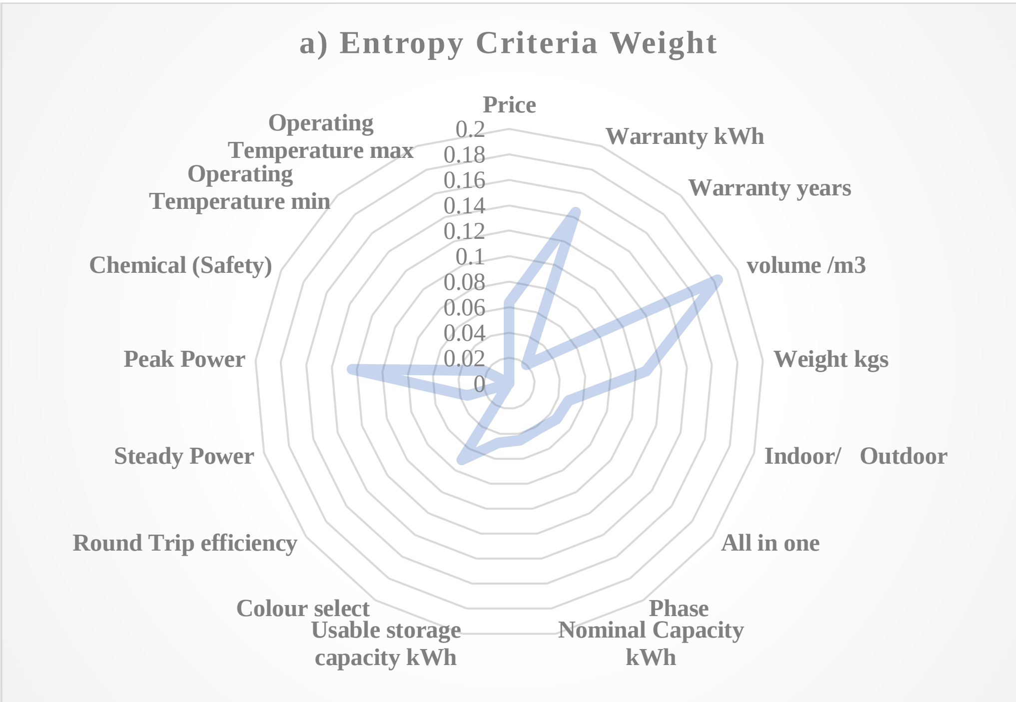
Figure 7: The graphical user interface of the ES Finder App; In the first column, the user identifies their preferences from rank 1 to 6 from a drop-down list. In the second column, if they wish they choose the method.

5 Case study

Energy storage technologies are being used by various users with different preferences and for diverse applications. The energy storage needs for a family living in a house with rooftop PV might be different from those living in an apartment. Likewise, the need of a working family with children is different from a retired family. The needs and preferences of a grocery shop are different from a hair salon, and so on. These differences are expected to show themselves in the preferences when selecting energy storage. In this section, user cases are explained. The first one is the weight entropy case, the second one is the small enterprise case, the third one is the university green building case. These three cases are discussed next.

Users without expertise (the use of weight entropy): In this case, we consider the scenario that the user does not have a proper understanding of energy storage technologies as well as

MCDM methodologies. As discussed in Section 4.4, entropy weight is a method that can automatically develop criteria weighting without the need for the user to provide any preference. Using the method discussed in Section 4.4., the criteria weights are obtained and shown in Figure 7a. With the selection of “All” button for methods (See Figure 7 middle column), the MCDM program is executed, and the storage recommendation list is provided as demonstrated in Figure 8. For this application, the E-KwBe 5.6, ELMOFO E-Cells ALB52-106, Super Lithium, DCS PV 5.0, and Powerwall 2 (AC) are found as the first to fifth top choices, respectively.



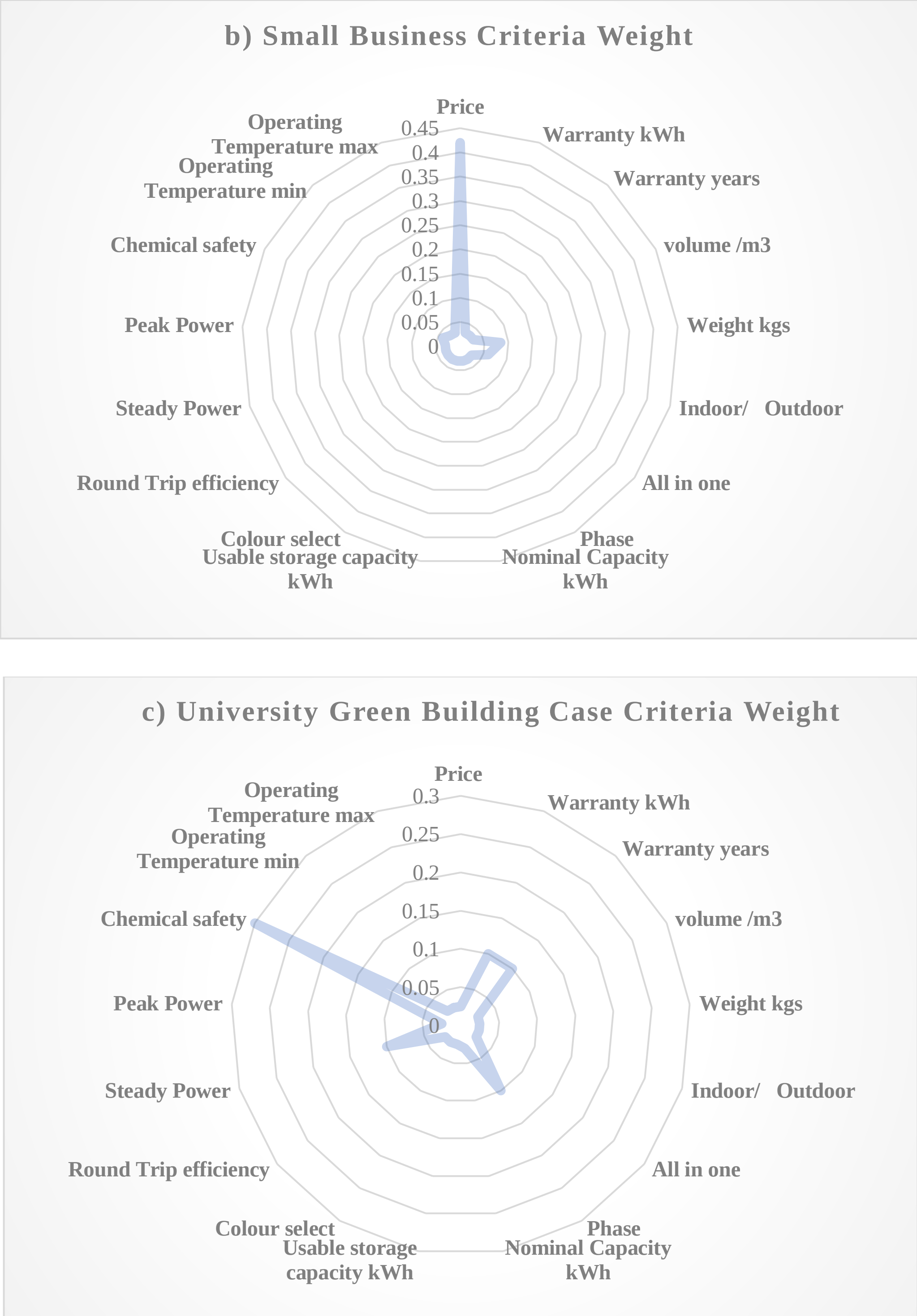


Figure 8: Criteria weight distribution for three cases: a) criteria weight entropy, b) small business, and c) a university green building

Small business: This case is regarding a small private enterprise for which cost reduction is a vital element in business operations. The company selects price as the first preference. Many small enterprises are located in an industrial park. As such, safe operation is their internal responsibility, but it also impacts the whole park. So, in this case, safety is listed as another property of concern. The location of EST installation needs to be considered indoors or outdoors due to the unstable lease of the plant that may result in relocation. In particular, products that are both indoor and outdoor can score highly in the evaluation. The relocation of energy storage products also requires consideration of weight, and the movement of lightweight products can save in costs. According to the description above, the criteria weights obtained are shown in Figure 7b.

The ranking of recommended products is shown in Figure 8 and according to the results, the top five are Super Lithium, DCS PV 5.0, E-KwBe 5.6, PHI 3.4 TM Smart-Tech Battery, Magellan HESS. Super Lithium, which was the third choice for the previous case, is now recommended as the first choice. This could be because the price of Super Lithium ranks fourth low in the database with a total of 27 products.

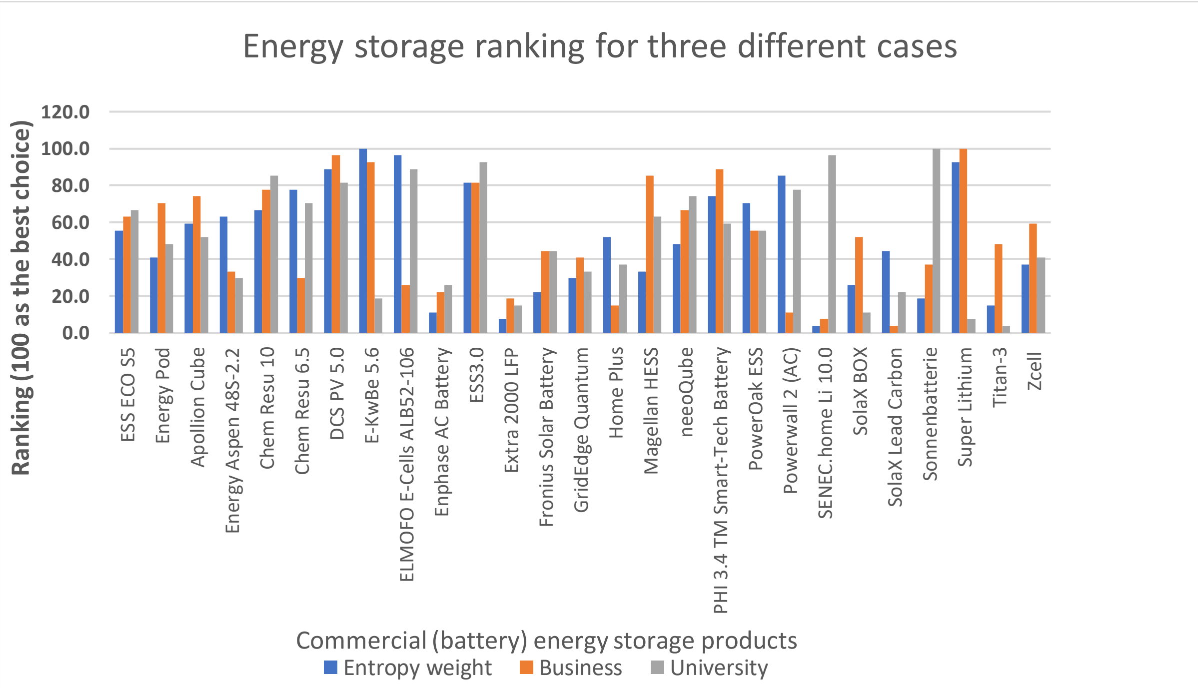


Figure 8: The energy storage ranking for three cases: a) criteria weight entropy, b) small business plant, and c) a university green building; the rank value of 100 reflects the most suitable choice.

University green building: Energy conservation and emission reduction are the characteristics of green buildings. For green educational buildings with a relatively high number of visitors, safety is the most important consideration. Therefore, the user selects the first three drop-down options as safety to highlight the importance of this attribute. Also being a green building, the selection of frequency conversion products can effectively reduce energy waste. In the fourth drop-down option, the phase is selected. As a university building, frequent construction or maintenance will affect the daily use of the building. To reduce the occurrence of this kind of situation, it is imperative to choose products with a long warranty period. As described above, the criteria weights obtained are shown in Figure 7c.

The result of the university green building case is shown in Figure 8. For this application, the Sonnenbatterie, SENEC.home Li 10.0, ESS3.0, ELMOFO E-Cells ALB52-106, Chem Resu 10 are found as the first to fifth top choices, respectively. These products are all rated high in terms of safety.

6 Conclusion

There is growing uptake of energy storage technologies by households and businesses because of the increasing uptake of distributed renewable energy technologies such as PV. Energy storage technologies can address the key challenge of renewable technologies inherent in their non-steady availability. Due to the diversity of commercial energy storage options and a large number of products on the market, the selection of the right technology is not an easy task since there are multiple attributes to be considered at the same time. In a non-supported situation, the decision-maker has to evaluate the attributes of the product holistically which can be very challenging and can result in a choice that is not the best possible one. In this paper, we have described and evaluated different multi-criteria decision-making methods which can be used to help the decision-maker in this kind of setting which can be supported by different methods. Because of the availability of diverse MCDM methods the selection of the right one, by itself is also an MCDM problem. This paper studied 13 methods of the conventional MCDM techniques and identified nine methodologies of AHP, SAW, CODAS, MABAC, COPRAS, TOPSIS, VIKOR, PROMETHEE, WSM&WOM for this study. We also identified 19 energy storage attributes and built a criteria structure for the modelling (See Figures 4 and 5). The programming was conducted in Matlab and we developed an “ES Finder” App, which upon the preference input by the users calculates the score of each product through the score ranking and determines the appropriate storage technologies. We also conducted a few case studies that showed the marked impact of the user preferences on the recommended best technology. Therefore, this project can significantly fill the gap for the growing demand-side energy storage users which are expected to be majorly nonexperts. Such tools can help them make the right decision and avoid wastage of resources.

There are a number of possible directions for future research. There is likely a need to expand the database and enable dynamic update of products’ specifications upon a new release, one could also analyse and include possible new MCDM methods. A relevant topic is also to consider the risks of behavioural and cognitive biases related to the use of the methods [65].

Nomenclature

Abbreviations

AHP	Analytical Hierarchy Process
ANP	Analytical Network Process
WSM & WPM	Weighted Sum Model & Weighted Product Model
SAW	Simple Additive Weighting
SMART	Simple Multi-Attribute Rating Technique
PROMETHEE	The Preference Ranking Organisation Method for Enrichment Evaluation
TOPSIS	Technique for Order of Preference by Similarity to Ideal Solution
CODAS	Combinative Distance-based Assessment
VIKOR	VIsekriterijumska optimizacija i KOmpromisno Resenje
MABAC	Multi-attributive Border Approximation Area Comparison
COPRAS	Complex Proportional Assessment
GRA	Grey Relational Analysis
GP	Goal Programming

Notation

d_i	Degree of diversification
e_i	Entropy for criterion *j*
i	alternative (1,2, 3,…*M*)
j	criterion (1,2, 3,…*N*)
M	Total number of alternatives
N	Total number of criteria
V_{ij}	Normalized matrix
iV_{ij}	Normalized matrix by inverting the unfavourable criteria
w_i	Entropy weight
x_{ij}	Array *ij* in the original decision matrix

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