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Ranking Energy Storage Technologies with VIKOR

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Various energy storage technologies are currently available to address the problem of renewable energy intermittency. Due to wide selection of energy storage technologies with contrasting characteristics, strengths, and weaknesses, selection of the most appropriate technology for a specific type of application is a daunting task. In this study, the multiple attribute decision-making method VIKOR (Vlse Kriterijumska Optimizacija Kompromisno Resenje) is used as a systematic approach for ranking available energy storage technologies. The competing technologies are evaluated based on energy density, power rating, discharge time, cycle efficiency, lifetime, and specific cost. Data for these various criteria are based on reports in the literature and are processed using the VIKOR algorithm. This study demonstrates that the lithium-ion battery is the best technology for energy storage of renewable energy with assessment index, Q = 0.16; it is followed closely by the sodium-sulfur battery, with Q = 0.17. The result of this study shows that VIKOR can be used to select the best energy storage technology for power generation and guide decision-makers on the most suitable technology for enabling the transition to a zero-carbon energy systems.

1. Introduction

The popularity of renewable energy (RE) has surged in the past few years due to the negative consequences of climate change resulting from the continued use of fossil fuels (Chofreh et al., 2020). Based on current trends, RE will play a key role in a clean energy landscape where it provides a reliable and continuous supply of electricity (Gielen et al., 2019). However, RE has its fair share of problems and challenges that hinders its full adoption and integration in the energy grid. One major issue is that RE suffers from intermittency, thus affecting its reliability as an alternative source of energy. In addition, RE such as solar energy and wind energy are usually located far from where it is consumed, causing high investment cost and transmission losses that increase the cost of electricity (Cole et al., 2021).

Energy storage is seen as a solution to this problem by providing a buffer between supply and demand. The energy can then be tapped in times of peak demand in electricity. Different energy storage technologies have been proposed, such as battery energy storage (BES), compressed air energy storage (CAES), pump hydro energy storage (PHES), flywheel energy storage (FWES), supercapacitor energy storage (SCES) and various thermal energy storage systems (TES) (Guney et al., 2017). A review of available energy storage technologies can be found in the paper by Rahman et al. (2020). However, selection of an optimal alternative is not an easy task because of the wide variety of alternatives and complex characteristics of these energy storage options.

Multi-attribute decision-making (MADM) methods have been applied in various fields for problems involving ranking multiple alternative based on a set of criteria (Gul et al., 2016). The criteria usually involve technical, economic, environmental, and social attributes, which may be conflicting and complex. The general approach involves the computation of an aggregate merit score (Sikdar, 2009). An example of MADM is VIKOR (Vlse Kriterijumska Optimizacija Kompromisno Resenje), an MADM method developed by Duckstein and Opricović (1980). VIKOR is based on ranking a set of alternatives based on criteria to determine the option closest to the ideal solution. VIKOR has been applied in various fields to aid in the decision-making process and several variations have been proposed such as comprehensive VIKOR, fuzzy VIKOR, regret theory-based VIKOR, modified VIKOR and interval VIKOR (Chatterjee and Chakraborty, 2016).

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Despite the popularity and potential of VIKOR, it has not been widely applied in ranking energy storage technologies in the literature. Therefore, to address this research gap, this paper applies VIKOR method as approach in selecting the relevant energy storage option for integration with renewable energy sources. No prior use of VIKOR has been reported in the literature for the six energy storage technologies selected for stationary power applications. It can be used as a guide for decision-makers in selecting the best energy storage option to adopt for their policy on clean and sustainable energy. The paper presents in Section 2 the problem statement, followed by the description of the VIKOR methodology in Section 3. It is then applied to a specific case on energy storage in Section 4. Then, Section 6 gives the summary and prospects for future work.

2. Problem Statement

The problem being addressed in this study can be expressed as follows:

- Given a set M of alternative energy technologies with respect to N criteria;
- Given that each alternative *i*(i = 1, 2, … m) has a set of values corresponding to the performance f_{ij} in the criterion *j*(j = 1, 2, … n);

The aim of the methodology is to determine the alternative with the minimal assessment index Q, and to rank the alternatives from the most optimistic (Q = 0) to the most pessimistic (Q = 1). The best alternative energy storage technology is the one with the least Q value.

3. Methodology

The MADM method used here is based on VIKOR (Opricović, 1990). From the given values of M alternative energy storage technologies with respect to N criteria, the minimum $\left[(f_{ij})_{min}\right]$ and maximum $\left[(f_{ij})_{max}\right]$ values are determined for each criterion in the decision-making matrix. Here, f_{ij} represents the rating of an alternative technology with respect to a criterion. These minimum and maximum values for each criterion are then used in the linearization and normalization of the scores for each energy storage technology.

$$N_{ij} = \frac{(f_{ij})_{max} - f_{ij}}{(f_{ij})_{max} - (f_{ij})_{min}} \tag{1}$$

The next step of the algorithm is to decide the weight of each criterion. This step is highly subjective as the weight assigned to each criterion depends on the prior knowledge of the decision-maker regarding the contribution of each criteria on the overall attractiveness of each energy storage technology. This is known as the subjective method of deciding weights (Tan et al., 2019). Alternatively, a procedure such as the Analytic Hierarchy Process (AHP) (Saaty, 1980) or the Best-Worst Method (BWM) (Rezaei, 2015) can be used to systematically elicit weights from expert inputs. In this work, the weights are assumed to be exogenously defined.

After the linearization and normalization of the values for each criterion, average group utility (S) and maximum regret (R) may now be evaluated using the following equations:

$$S_i = \sum_{j=1}^{n}\left[w_j \frac{(f_{ij})_{max} - f_{ij}}{(f_{ij})_{max} - (f_{ij})_{min}}\right] \qquad i = 1, 2, \ldots m \tag{2}$$

$$R_i = Max\left[w_j\left(\frac{(f_{ij})_{max} - f_{ij}}{(f_{ij})_{max} - (f_{ij})_{min}}\right)\right] \qquad i = 1, 2, \ldots m \tag{3}$$

For non-beneficial criteria where the desired are the lower values, the expression $(f_{ij})_{max} - f_{ij}$ is replaced by $f_{ij} - (f_{ij})_{min}$(Wang et al., 2019):

$$S_i = \sum_{j=1}^{n}\left[w_j \frac{f_{ij} - (f_{ij})_{min}}{(f_{ij})_{max} - (f_{ij})_{min}}\right] \tag{4}$$

After the determination of S and R values, assessment index (Q) is evaluated. In the determination of Q, a parameter v is needed, which is the maximum group utility; 1 – v, on the other hand is known as the weight of regret. The value of parameter v reflects the degree of optimism of the decision-maker. The minimum and maximum values for each criterion are also determined and are incorporated in the equation for the determination of Q:

$$Q_i = v\left[\frac{S_i - (S_i)_{min}}{(S_i)_{max} - (S_i)_{min}}\right] + (1 - v)\left[\frac{R_i - (R_i)_{min}}{(R_i)_{max} - (R_i)_{min}}\right] \quad (5)$$

The Q values are then summarized, and each energy storage technology is ranked based on the same scale, with smaller values being more desirable. The best energy storage technology is the one with the least Q value among the different alternatives. However, additional decision criteria are used to assess the degree of separation of the best alternative from the second best, and to gauge the stability of the solution with respect to parameter v (Opricović and Tzeng, 2007). The details of the procedure are omitted here.

4. Case Study

The transition to a clean, reliable and stable energy source through RE can be achieved with the application of energy conversion and storage. Several technologies are available to store excess energy produced during lean electricity demand. The technologies can be classified as electrochemical, mechanical, electrostatic, thermal, thermochemical, magnetic and chemical energy storage (Sterner and Bauer, 2019). In this study, several electrochemical and mechanical energy storage, and one electrostatic energy storage technology are considered as summarized in Table 1.

Among the eight energy storage technologies, four are classified as electrochemical (Li-ion battery, Na-S battery, Pb-acid battery and Ni-Cd battery); three are mechanical energy storage technologies – pumped hydro energy storage (PHES), flywheel energy storage (FES) and compressed air energy storage (CAES); and one is electrostatic – supercapacitor energy storage (SCES). The criteria for the eight energy storage technologies are based on the report of Koohi-Fayegh and Rosen (2020) as shown on Table 1. The attributes are volumetric power density (kW/m^3), volumetric energy density (kWh/m^3), mass energy density (kWh/t), cycle efficiency (%), life (number of charge cycles), power capital cost ($/kW), and energy capital cost ($/kWh).

Table 1: Performance of various energy storage technologies

Energy Storage Technology	Volumetric power density (kW/m^3)	Volumetric Energy Density (kWh/m^3)	Mass energy density (kWh/t)	Cycle efficiency (%)	Life (log n)	Power capital cost ($/kW)	Energy capital cost ($/kWh)
SCES	15	1	0.05	60	4	515	10,000
FWES	40	0.3	5	70	4	2,200	8,800
PHES	0.01	0.2	0.2	65	3.7	4,600	300
CAES	0.04	0.4	3	41	4	1,500	50
Li-ion battery	60	90	30	70	2.7	4,000	2,500
Ni-Cd battery	40	15	10	60	2.5	15,000	1,500
Na-S battery	1	150	100	70	3	3,000	500
Pb-acid battery	10	25	10	65	2	600	400

The maximum and minimum value in Table 1 are determined for each criterion. High values for volumetric power density, volumetric energy density, mass density, cycle efficiency and cycle life are desirable since compact, efficient and long cycle life are good characteristics for RE storage. In contrast, for power capital cost and energy capital cost, low values are preferred since it entails low capital expenditures per kW or kWh of power/energy generated. Using Eq(1), the value for each energy storage technology in every criterion is normalized. The summary is presented in Table 2.

The closer the value of the storage technology to 0 the better is the performance for that specific criterion. On the other hand, the technology has worse performance if the value is closer to 1. It can be noted in Table 2 that majority of the mechanical energy storage technologies have values closer to 1 relative to the performance of electrochemical energy storage technologies. Mechanical energy storage technologies such as PHES, CAES and FWES, usually require more space for the installation of these technologies. Specifically, PHES and CAES require more water and air in direct proportion to the amount of energy to be stored. On the other hand, battery energy storage technologies are more compact and require fewer quantity of the active materials to store the same amount of energy. In this regard, for space-constrained applications such as urban areas, battery electrochemical energy storage technologies are preferable since these technologies are energy-dense and can be easily deployed.

It is also worth noting in Table 2 that FWES has excellent performance in terms of cycle efficiency and cycle life. This technology is very attractive because of these advantages, but it currently suffers from lower volumetric

energy density and mass density. More research effort is required to improve the performance of this technology in these criteria.
In terms of power capital cost and energy capital cost, PHES, CAES and Pb-acid battery are the clear winners based on the normalized values in Table 2. These technologies require lower capital and operating expenses per kW/kWh of energy generated. In addition, PHES and CAES have relatively long cycle life as reflected in Table 1. However, these technologies are advantageous for places with an abundance of tract of land or caverns where water can be moved to higher elevation or compressed air can be stored. The disadvantage is clearly seen in the values of PHES and CAES for volumetric power density, volumetric energy density and mass density criteria as shown in Table 1. These technologies have relatively low volumetric and gravimetric energy density.

Table 2: Normalized value of each energy storage technology with respect to a criterion

Energy Storage Technology	Volumetric power density	Volumetric Energy Density	Mass energy density	Cycle efficiency	Life	Power capital cost	Energy capital cost
SCES	0.75	0.99	1.00	0.34	0.00	0.00	1.00
FWES	0.33	1.00	0.95	0.00	0.00	0.12	0.88
PHES	1.00	1.00	1.00	0.17	0.15	0.28	0.03
CAES	1.00	1.00	0.97	1.00	0.00	0.07	0.00
Li-ion battery	0.00	0.40	0.70	0.00	0.65	0.24	0.25
Ni-Cd battery	0.33	0.90	0.90	0.34	0.75	1.00	0.15
Na-S battery	0.98	0.00	0.00	0.00	0.50	0.17	0.05
Pb-acid battery	0.83	0.83	0.90	0.17	1.00	0.01	0.04

The average group utility (S) is then determined by getting the summation of the normalized values in Table 2 for each energy storage alternative. On the other hand, the maximum regret value (R) is the worst performance of each alternative storage technology across the various attributes being compared. It is assumed here that equal weights are assigned to the criteria. The S and R values for each alternative are reflected in Table 3.

Table 3: S and R value for each energy storage technology

Energy Storage Technology	S	R
SCES	0.58	1.00
FWES	0.47	1.00
PHES	0.52	1.00
CAES	0.58	1.00
Li-ion battery	0.32	0.70
Ni-Cd battery	0.63	1.00
Na-S battery	0.24	0.98
Pb-acid battery	0.54	1.00

The average group utility (S) values in Table 3 are then normalized using the formula $\left[\frac{S_i-(S_i)_{min}}{(S_i)_{max}-(S_i)_{min}}\right]$ from Eq(5). Similarly, R values are normalized using the formula $\left[\frac{R_i-(R_i)_{min}}{(R_i)_{max}-(R_i)_{min}}\right]$. The result of the normalization of values is summarized in Table 4.

Table 4: Normalized S/R value and Q value for each energy storage technology

Energy Storage Technology	S	R	Q	Rank
SCES	0.89	1.00	0.91	7
FWES	0.59	1.00	0.66	3
PHES	0.72	1.00	0.77	4
CAES	0.87	1.00	0.90	6
Li-ion battery	0.20	0.00	0.16	1
Ni-Cd battery	1.00	1.00	1.00	8
Na-S battery	0.00	0.94	0.17	2
Pb-acid battery	0.78	1.00	0.82	5

Q values in Table 4 are calculated using Eq(5), with a maximum group utility v = 0.82. The energy storage technologies are ranked with the most optimistic value = 0 and pessimistic = 1. Based on this scale it can be observed that lithium-ion battery is the best (lowest Q = 0.16) and Ni-Cd battery is the worst (highest Q = 1.00). The advantages of lithium-ion battery are associated with its high volumetric power density, high volumetric energy density and high mass density. It entails less amount of material and space requirement for a given quantity of energy stored or power delivered by the device. In addition, the cells can be packed in modules such that it is easier for it to be moved to another location to augment capacity. These advantages stand in contrast with the high self-discharge rate and lower volumetric and gravimetric energy capacity of Ni-Cd. The compactness of lithium-ion battery is very much preferred for applications in highly-populated urban centres as compared to CAES and PHES technologies. It is also worth noting the Q value (Q = 0.17) for Na-S battery, which is very close to lithium-ion battery. Na-S chemistry is an emerging battery technology. It could rival lithium-ion battery in stationary power, transportation, and various other applications.

5. Conclusions

This study implemented VIKOR methodology in ranking eight energy storage technologies for stationary power applications. The result of the minimization of the assessment index Q based on the S and R values shows that lithium-ion battery technology is the best option for renewable energy storage. It is followed closely by the emerging energy storage technology based on sodium-sulfur chemistry (Na-S battery). On the other hand, Ni-Cd battery is the worst technology due to relatively low volumetric and gravimetric energy density and high power capital cost. The methodology can be adjusted such that weights for the attributes on cost per kW or cost per kWh can be given more emphasis to reflect the importance of economics on the decision-making process. This is the case for places with an abundance of tract of land, mountainous topography or presence of caverns where mechanical energy storage technologies such as PHES and CAES can be deployed. However, for space-constrained locations battery storage technologies, specifically lithium-ion battery, will be the dominant option for energy storage. This study shows that MADM can guide decision-makers in selecting the appropriate energy storage technology based on several alternatives. Future work can extend this analysis by including additional storage technologies and additional environmental criteria, particularly resource depletion and waste generation. Criteria weights can be calibrated using appropriate methods such as BWM or AHP. Stochastic, fuzzy, or interval extensions can also be developed to account for uncertainties in the data.

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