A DEEP DIVE INTO ENERGY STORAGE ALTERNATIVES

Fatemeh Rostami, Youssef Elomari, Laureano Jiménez, Carlos Pozo*

Departament d'Enginyeria Quimica, Universitat Rovira i Virgili, Av. Països Catalans 26, 43007 Tarragona, Spain

*Corresponding Author: carlos.pozo@urv.cat

ABSTRACT

This study evaluates the crucial role of energy storage in aligning electricity supply with demand. We compare 25 storage alternatives through the lens of sustainability. We use Data Envelopment Analysis (DEA), a linear programming method that allows assessing the relative performance of a set of options considering multiple indicators. Separate analyses are performed for medium and long-term options. In the former, we examine nine battery types and, in the latter, 16 power-to-hydrogen/ammonia routes. The evaluation spans economic, environmental, and social dimensions, encompassing key indicators like the levelized cost of energy, energy, and water usage, global warming potential, and employment opportunities. Implicitly, DEA assumes equal importance among all the indicators considered. Hence, we provide an additional analysis prioritizing environmental aspects. In our results, nickel-cadmium batteries with median performance score of 1.5 stand out in the medium-term cluster, while green hydrogen and ammonia powered by renewable sources take the lead in the long-term, even in the analysis favoring environmental indicators. Quantitative improvement targets are also provided for less efficient options, with implementation potential contingent upon their Technology Readiness Levels. For instance, redox flow batteries need at least 80% reduction in their input parameters to be efficient. The results offer valuable insights for policymakers, investors, and energy planners to integrate efficient and sustainable options, fostering cleaner and more resilient energy portfolios.

1 INTRODUCTION

Electricity is a crucial foundation supporting most economic activities and influencing human living conditions. The complex electricity systems connect generators with consumers through transmission and distribution grids. Historically, the focus of designing secure electricity systems revolved around technical parameters such as stability, flexibility, resilience, adequacy, and robustness (Blanco & Faaij, 2018). As a result, dispatchable technologies, primarily rooted in fossil fuels or nuclear energy, were used to ensure a dependable energy supply.

Growing environmental concerns have recently prompted the adoption of clean and renewable electricity production technologies. However, the inherent intermittency, long-term unpredictability, and short-term uncertainty of renewable sources like solar and wind pose challenges in aligning energy supply with fluctuating demand. Energy storage emerges as a crucial solution to address this disparity, converting electricity into storable forms for release into the network when needed. Beyond ensuring reliability, efficiency, safety, security, and grid stability (Ming et al., 2019; Mostafa et al., 2020), energy storage minimizes the cost of electricity supply by reducing interruptions (IRENA, 2020).

In the context of a projected shift in global power generation with renewable to 86% by 2050, up from 25% in 2020 (IRENA, 2020), energy storage becomes essential for the energy sector's decarbonization. Storage alternatives, although various, differ in function, duration, and stored energy form. Hence, diverse energy storage technologies with varied characteristics are crucial to cater to diverse applications. Acknowledging that there is no "one-fits-all" solution, meeting economic, environmental, and technical targets is imperative to facilitate the development and deployment of energy storage technologies.

https://doi.org/10.52202/077185-0184

While previous works have compared energy storage technologies based on economic, technical, or environmental aspects, a comprehensive assessment should include economic, environmental, and social perspectives concurrently. Some studies examined only life cycle costs, highlighting the impact of power conversion components (Zakeri & Syri, 2015), others evaluated storage technologies based on energy density, cycle efficiency, and lifetime (Akram et al., 2020), while others shifted the attention to environmental concerns through a life cycle assessment method (Fernandez-Marchante et al., 2020).

This contribution aims to bridge this gap by evaluating a wide range of energy storage technologies using six key performance indicators. These indicators cover sustainability dimensions comprehensively, allowing for a holistic comparison of nine medium-term and 16 long-term storage options. Notably, this assessment includes an analysis of ammonia as an energy storage material and incorporates the operational phase of storage technologies.

To compare options considering multiple sustainability indicators, this study employs Data Envelopment Analysis (DEA). DEA combines various indicators into a single score, commonly known as performance score (Rostami et al., 2022), classifying technologies as either efficient or inefficient. DEA is already applied as a multi-criteria decision-making tool in the context of energy (Cabrera-Jiménez et al., 2022). It also expands on previous efforts by providing quantified improvement targets for inefficient technologies that, if attained, would make them efficient. These targets offer valuable insights for researchers and technology developers, pointing on the direction of change for their designs. In addition, acknowledging that implementing improvements targets is challenging for mature technologies, we discuss the results obtained in the context of the Technology Readiness Level (TRL).

One of the strengths in DEA is the ability to combine multiple indicators in the absence of predefined weights. In practice, this is equivalent to assuming equal importance among the indicators considered. However, in practice, stakeholders may prioritize certain facets of sustainability when making their decisions. Recognizing this, we present an additional analysis using DEA but assigning greater importance to environmental indicators, thus prioritizing cleaner technologies for a sustainable energy transition. Overall, our analysis builds upon DEA's proven utility in benchmarking various engineering systems in the energy sector.

The following section delves into the methodology applied for the multicriteria assessment of energy storage technologies, while the third section presents and discusses the results obtained. Finally, the fourth section examines how these findings can guide effective policymaking.

2 METHODS

This section presents the methodology used to assess and compare the performance of different energy storage technologies from the economic, environmental, and social perspectives. Initially, we introduce the concept of DEA methodology, followed by the introduction of the specific indicators used and their uncertainty analysis approach. Subsequently, we present the DEA model chosen. Lastly, we described the alternative DEA model employed to explore the effect of emphasizing environmental indicators.

2.1 DEA Overview

DEA is a linear programming method used to measure the relative performance of the so-called Decision-Making Units (DMUs) in transforming inputs into outputs. Our application of DEA focuses on energy storage technologies. In this context, we model energy storage technologies as DMUs, and the sustainability metrics as their inputs and outputs. To account for the diverse nature of storage technologies, these are grouped into medium-term and long-term options based on their duration and frequency of power supply. Table 1 presents this classification and the items considered. Long-term options are further subdivided into three categories based on the type of power source used in the production route (green, blue, and grey). Notably, large scale mechanical energy storage options and thermal alternatives are excluded do to data limitation.

https://doi.org/10.52202/077185-0184

Table 1: Energy storage alternatives and their classifications.

Medium-term		Long-term	
Alternatives	**Symbol**	**Alternatives**	**Alternatives**
Lead acid	LA		
Lithium-ion	Li-ion	H_2, Hydropower[gr]	NH_3, WSCL[3, b]
Lithium iron phosphate	LiFePh	H_2, Solar[gr]	H_2, CG[4, g]
Lithium nickel manganese cobalt	LiNiMnCo	H_2, Wind[gr]	H_2, Grid mix[g]
Nickel-cadmium	NiCd	NH_3, Hydropower[gr]	H_2, SMR[4, g]
Sodium nickel chloride	NaNiCl	NH_3, Solar[gr]	H_2, WSCL[3, g]
Sodium sulphide	NaS	NH_3, Wind[gr]	H_2, CG-CCS[2, 4, g]
Vanadium redox flow battery	VRFB	H_2, SMR-CCS[1, 2, b]	NH_3, Grid mix[g]
Zinc bromine flow battery	ZBFB	NH_3, SMR-CCS[1, 2, b]	NH_3, SMR[4, g]

1: Steam methane reforming, 2: Carbon capture and storage, 3: Water splitting by chemical looping, 4: Coal gasification.
gr: Green, renewable energies as energy source; b: Blue, fossil fuels combined with carbon capture and storage as energy source; g: Grey, fossil fuels (or the grid, sometimes referred to as yellow) as energy source.

2.2 Inputs and outputs

We have chosen six performance indicators to encompass economic, environmental, and social dimensions, outlined as follows. Note that these can be classified either as inputs, desired outputs, or undesired outputs of the DMUs. In DEA, lower levels of inputs and undesirable outputs are preferable, while options with higher levels of outputs are sought.

- Electricity consumption [GJ] (Input): This metric is associated with emissions and serves as an environmental indicator (Mukelabai et al., 2021).
- Energy density [GJ/kg] (Input): This provides insights into material requirements and technology size. It is employed for medium-term alternatives. Note that we use its inverse term (1/energy density) as an input to be minimized (Zakeri & Syri, 2015).
- Employment [FTEJ] (Desired output): Reflecting the creation of full-time equivalent jobs necessary for the development of options within each group, this indicator functions as a social measure (Rostami et al., 2022).
- Global Warming Potential, GWP [CO_2-eq Emissions] (Undesired output): As an environmental indicator, resulted by the electricity from non-renewable sources used to produce the storage options, mirrors the greenhouse gas emissions resulting from the development of storage alternatives (Siddiqui & Dincer, 2019).
- Levelized Cost of Storage, LCOS [€/GJ] (Input): For medium-term options, this metric encompasses initial, variable, and end-of-life costs (Zakeri & Syri, 2015). In the case of long-term options, it represents the cost of producing one kilogram of hydrogen or ammonia (Thengane et al., 2014).
- Water usage [m^3] (Input): Functioning as an environmental indicator, it represents the water used in the development of each medium-term option or one kilogram of H_2 or NH_3 (Chisalita et al., 2020).

We employ uncertainty distributions to manage data variability. Specifically, we use three types of distributions in our analysis, including uniform distributions for parameters with a single literature value, and triangular distributions for parameters with a range of values. For GWP, a life cycle indicator, uncertainties are characterized following guidelines from the Ecoinvent database, i.e., employing individual lognormal distributions based on the so-called Pedigree Matrix. The details of the Pedigree Matrix are introduced elsewhere (Barnosell & Pozo, 2024). After establishing uncertain distributions for various parameters, Monte Carlo sampling is employed to discretize these distributions (Frutiger et al., 2018), generating 100 independent scenarios for each indicator. Subsequently, a DEA model is solved for each scenario of each DMU, resulting in 100 distinct performance scores for each DMU.

2.3 DEA Model

Without loss of generality, we employ the non-oriented undesired output slack-based model for evaluating the performance scores of DMUs (H. Li et al., 2013). This model is presented in equations (1)-(6). DMUs achieving a performance score of one are considered efficient and form the so-called efficient frontier. Meanwhile, DMUs with a score ranging from 0 to 1 are deemed inefficient.

https://doi.org/10.52202/077185-0184

One well-known drawback of traditional DEA models is that all the efficient DMUs get a score of one, which prevents further ranking between them. To address this challenge, the slack-based super-efficiency DEA model for undesired outputs allows to distinguish the performance of efficient DMUs. In DEA super-efficiency models, the DMU under evaluation is excluded from the pool of candidate DMUs forming the efficient frontier, which allows the DMU to achieve efficient scores above one. This allows to rank efficient DMUs, providing further insights into the potential enhancements of efficient options. The specifics of the super-efficiency model are not presented here, but can be found elsewhere (Fang et al., 2013).

$$\tau^* = \min t - \frac{1}{m} \sum_{i=1}^{m} \frac{S_i^-}{x_{io}} \tag{1}$$

$$\text{s.t.} \qquad 1 = t + \frac{1}{s_1+s_2}\left(\sum_{r=1}^{s_1} \frac{S_r^g}{y_{ro}^g} + \sum_{r=1}^{s_2} \frac{S_r^b}{y_{ro}^b}\right) \tag{2}$$

$$x_o t = X\Lambda + S^- \tag{3}$$

$$y_o^g t = Y^g \Lambda - S^g \tag{4}$$

$$y_o^b t = Y^b \Lambda + S^b \tag{5}$$

$$S^- \geq 0,\ S^g \geq 0,\ S^b \geq 0,\ \Lambda \geq 0,\ t > 0. \tag{6}$$

The performance score of a DMU under assessment is denoted by τ^*. The Charnes-Cooper linear transformation coefficient (variable t) is introduced to convert the original nonlinear slack-based model for undesired outputs into a linear format (as already presented here). In this framework, m, s_1, and s_2 represent the numbers of inputs, desired outputs, and undesired outputs, respectively, for the DMUs assessed. Subscript i refers to inputs, while subscript r relates to outputs. Slack variables S_i^-, S_r^g, and S_r^b quantify the distance from each DMU to the efficient frontier in inputs, desired outputs, and undesired outputs, respectively. For efficient DMUs, these values will be zero; for inefficient ones, they indicate the improvements necessary for the DMU to achieve an efficient status. Parameters x_{io}, y_{ro}^g, and y_{ro}^b refer to the values of input, desired output, and undesired output of DMU o, respectively. X is the inputs matrix, while Y^g and Y^b are the corresponding matrices for desired and undesired outputs. The weight Λ combines efficient DMUs to create the so-called virtual DMU, an efficient version of the evaluated DMU evaluated, achieved by projecting the inefficient DMU onto the efficient frontier. The virtual DMU is used as reference by the model to compute the improvement targets. Notably, as presented by equation 6, variables should be positive since a negative value is meaningless.

There are some important remarks that need to be considered at this point. As aforementioned, DMUs are classified into two different clusters. Hence, the previous model needs to be applied to each DMU, considering only the energy storage options within the corresponding cluster. In addition, parameters x_{io}, y_{ro}^g, and y_{ro}^b will present different values in each of the 100 scenarios generated. Hence, each analysis needs to be carried out multiple times, one for each scenario. This will result in a distribution of performance scores (rather than a single value) for each of the DMUs analyzed.

2.4 Weighted model

As explained in the introduction, the previous DEA model implicitly assumes that all indicators are equally important. This might not be in agreement with an environmentally conscious stakeholder. To explore such a scenario, we next allocate 80% of the total weight to environmental aspects and distribute the remaining 20% evenly between economic and social indicators. This weight distribution is applied equally across indicators within each sustainability dimension. For medium-term technologies, each of the four environmental indicators receives a weight of 20% (80 divided by 4 equals 20). In the case of long-term alternatives, the three environmental indicators are assigned a weight of 26.67% each (80 divided by 3). Both clusters allocate 10% weight to LCOS and employment, the only indicators in the

https://doi.org/10.52202/077185-0184

economic and social categories, respectively. Subsequently, we modify the undesired output slack-based model (i.e., the model introduced in the previous section) to incorporate these weights as parameters: ω_i^- for inputs, ω_r^g for desired (good) outputs, and ω_r^b for undesired (bad) outputs. This revised model (see Equations (7)-(16)) is a weighted slack-based model as detailed in Tone (2011), where all other parameters and variables remain consistent with the previous model. Again, an equivalent (weighted) super-efficiency model is used to rank efficient DMUs. These weighted models are also executed for each DMU in each cluster, across the 100 scenarios.

$$\tau^* = \min t - \frac{1}{m} \sum_{i=1}^{m} \frac{\omega_i^- S_i^-}{x_{io}} \tag{7}$$

$$\text{s.t.} \quad 1 = t + \frac{1}{s_1+s_2}\left(\sum_{r=1}^{s_1} \frac{\omega_r^g S_r^g}{y_{ro}^g} + \sum_{r=1}^{s_2} \frac{\omega_r^b S_r^b}{y_{ro}^b}\right) \tag{8}$$

$$x_o t = X\Lambda + S^- \tag{9}$$

$$y_o^g t = Y^g \Lambda - S^g \tag{10}$$

$$y_o^b t = Y^b \Lambda + S^b \tag{11}$$

$$\omega_i^- = 0.2 \qquad \forall\ i = \left\{energy\ consumption, water\ used, \frac{1}{energy\ density}\right\} \tag{12}$$

$$\omega_{r=GWP}^b = 0.2 \tag{13}$$

$$\omega_{i=LCOE}^- = 0.1 \tag{14}$$

$$\omega_{r=Employment}^g = 0.1 \tag{15}$$

$$S^- \geq 0,\ S^g \geq 0,\ S^b \geq 0,\ \Lambda \geq 0,\ t > 0. \tag{16}$$

3 RESULTS AND DISCUSSION

Section 3.1 delves into the interpretation of DEA results within the framework of the TRL across different technologies and alternatives. Then, section 3.2 provides improvement targets for DMUs identified inefficient, offering actionable guidelines for technology developers. Lastly, section 3.3 presents the effect of increasing the weights assigned to environmental indicators.

3.1 Identifying efficiencies and development potentials

Figure 1 illustrates the distribution of performance scores for the medium-term cluster across 100 scenarios, represented using a violin plot. Wider sections of the violins indicate performance scores with a higher probability of occurrence.

NiCd, Li-ion, and NaS batteries rank among the top three medium-term alternatives, with median performance scores of 1.61, 1.36, and 1.32, respectively. Conversely, ZBFB and VRFB exhibit notably low median performance scores (i.e., below 0.07 and 0.03), respectively, making them the least efficient technologies.

Despite being the preferred option here, the production of NiCd batteries could be limited by cadmium availability. This element is mostly obtained as a byproduct of zinc production processes, which poses concerns about its potential supply volume, in addition to human health hazards (Van den Bossche et al., 2006). Conversely, sodium batteries capitalize on sodium's cost-effectiveness, non-toxicity, and high recyclability potential, positioning them as promising contenders for high-power applications (Kumar et al., 2021; Van den Bossche et al., 2006). Still technical enhancements are necessitated to

https://doi.org/10.52202/077185-0184

address challenges such as low conductivity, cathode volume expansion, and anode corrosion by electrolytes (Zhang et al., 2020). Further, Li-ion battery variants (e.g., Li-Fe-Ph or Li-Ni-Mn-Co) are efficient in some scenarios. However, there are other scenarios where their performance may drop to 0.34 and 0.31, respectively. Despite challenges, lithium batteries, widely used in electric vehicles, demonstrate satisfactory performance across the sustainability indicators examined, with median performance scores ranging from 0.99 to 1.36. Li-ion achieves a higher median performance score (1.36 vs. 1.32) and a higher maximum performance score (1.53 vs. 1.43), suggesting that Li-ion can perform bet- ter than Na-S batteries in the most optimistic scenarios. A risk-taker pol- icy/investor may be inclined towards Li-ion batteries, capable of achiev- ing better performance. In contrast, a risk-averse policy/investor will bet on Na-S, as there is "no risk "of it being a non-competitive technology.

While a technology may appear favorable based on selected indicators, not all energy storage technologies successfully penetrate the market. The TRL, graded on a scale of 1 to 9, provides insights into the maturity and expected future developments of a technology. Technologies below TRL 4 are typically in research or conceptual testing phases, with TRL 4 to 6 indicating demonstration or technical development stages. TRLs above 7 denote specific certification tests or market readiness, nearing a TRL of 9 (GIA, 2022). Technologies at lower TRLs, while potentially promising for further development, face uncertainties regarding market penetration. On the other hand, the development potential of a technology declines as it matures (Ntavarinos et al., 2019). For instance, NiCd, Li-ion, Li-Fe-Ph, and potentially Li-Ni-Mn-Co batteries, are efficient options. However, as they are already marketable, they are not expected to have much room for improvement at this point. On the other hand, LA batteries show low performance scores despite being an already mature technology. Hence, achieving the improvement targets outlined in the subsequent section may prove challenging for this option. Technologies like Na-Ni-Cl, ZBFB, and VRFB, neither efficient nor marketable, require significant improvement before attaining efficiency. Nonetheless, their potential transition to the "efficient and marketable" category remains possible, considering the still possess a high development potential.

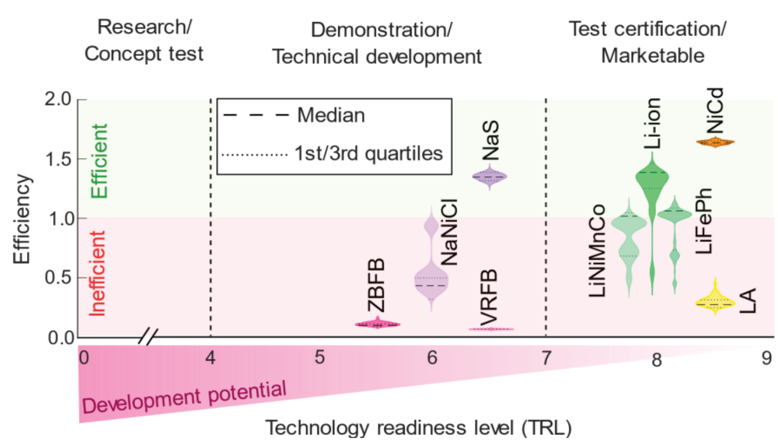

Figure 1: Distribution of performance scores for medium-term energy storage technologies under uncertainty. The horizontal axis presents the maturity of technologies as based on their TRL.

Figure 2 displays the performance scores for long-term energy storage alternatives. Green ammonia from solar energy is the only consistently efficient long-term option, attaining a median performance of 1.26. Green hydrogen from solar energy and then wind energy follow closely, boasting median performance scores of 1.09 and 1.08, respectively. The former capitalizes on low energy consumption, while the latter presents significant employment opportunities. Green ammonia derived from hydropower and wind energy rank fourth and fifth, with median efficiencies of 1.07 and 1.02, respectively.

https://doi.org/10.52202/077185-0184

These findings underscore that the top five long-term storage alternatives are aligned to water electrolysis using renewable energies, namely green hydrogen, and green ammonia. Also, options such as green hydrogen using hydropower, ammonia produced through water electrolysis using grid mix energy, and ammonia generated via chemical looping processes still have a chance of achieving efficiency despite exhibiting median efficiencies below one: 0.53, 0.44, and 0.39, respectively.

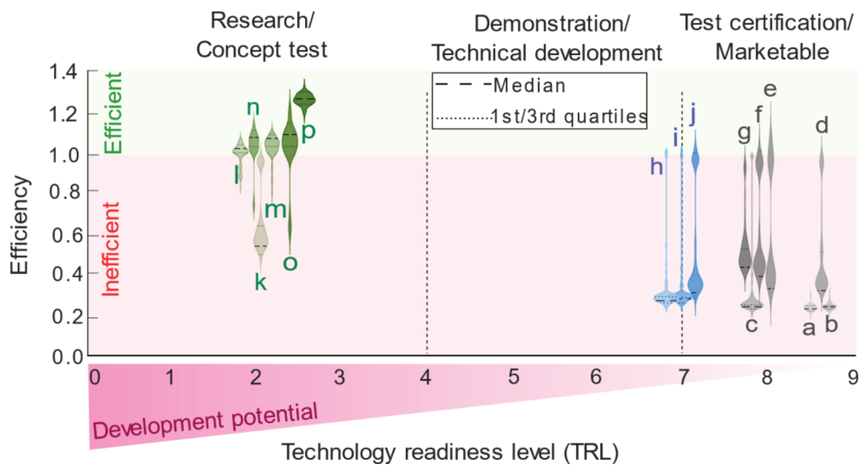

Figure 2: Distribution of performance scores for long-term energy storage alternatives under uncertainty. The horizontal axis presents the maturity of technologies as based on their TRL. Alternatives in increasing order of their median performance score: a: H_2, CG – b: H_2, SMR – c: H_2, WSCL – d: NH_3, SMR – e: H_2, Grid mix – f: NH_3, WSCL – g: NH_3, Grid mix – h: H_2, SMR-CCS – i: H_2, CG-CCS – j: NH_3, SMR-CCS – k: H_2, Hydropower – l: NH_3, Wind – m: NH_3, Hydropower – n: H_2, Wind – o: H_2, Solar – p: NH_3, Solar.

Transitioning to any of the remaining eight long-term storage alternatives significantly drops median performance scores, all falling below 0.33. This indicates their inferiority compared to the top eight options across the sustainability indicators considered. Furthermore, their GWP and substantial energy and water consumption further exacerbate their competitiveness, necessitating significant enhancements.

Reliable and explicit reporting of TRL for many long-term storage options is lacking in the literature. However, TRL for grey processes typically ranges from 8 to 9, exceeding that of blue processes, which usually range from 6 to 8. Lastly, green processes, with TRLs of 1-3 (THE ROYAL SOCIETY, 2018), have considerable progress ahead of them. Despite their current high costs compared to grey and even blue alternatives, future cost reductions in renewable energy sources are anticipated to render green alternatives the most economical options (Newborough & Cooley, 2020).

3.2 Identifying inefficiencies and development potentials

This section focuses on inefficient technologies, where improvement targets indicate the minimum reduction needed to render them efficient. Figure 3 illustrates the average improvement targets for inefficient medium-term technologies across the 100 scenarios. VRFB and ZBFB necessitate approximately a 90% reduction in their input and in GWP to attain efficiency. Given that these batteries are still in the demonstration stages of development (TRL of 6 out of 9), such improvement may be achievable. Two other technologies require substantial improvements to achieve the efficient status. The first is LA, with improvement targets exceeding 40% for LCOS, energy consumption, and energy density, and surpassing 90% for water usage and GWP. The second is Na-Ni-Cl, requiring targets of around 20% for LCOS and energy density, 40% for energy consumption, and over 70% for water usage and GWP. Conversely, Li-Fe-Ph and Li-Ni-Mn-Co, with average improvement targets of 8% and 14%,

https://doi.org/10.52202/077185-0184

respectively, show a promising potential for efficiency. To achieve this, they should primarily reduce their GWP by 23% and 35%, respectively. Additionally, the LCOS of these batteries requires improvements exceeding 5% for Li-Fe-Ph and over 9% for Li-Ni-Mn-Co. The cost reductions are well within reach given the extensive research on these batteries. Lastly, Li-ion technology demonstrates near-consistent efficiency, resulting in minimal improvement targets (consistently below 6%).

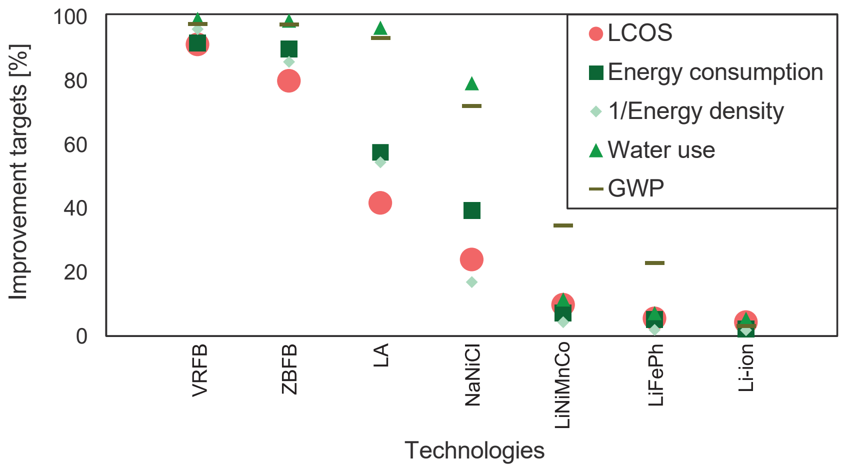

Figure 3: Improvement targets for medium-term technologies under uncertainty. The improvement target for each indicator and technology is estimated using the average of the 100 scenarios.

Improvement targets are then calculated for long-term alternatives observed inefficient in one or several scenarios. As depicted in Figure 4, the minimum reduction required in LCOS is below 1%, associated with "H_2, WE-Wind", a target that could naturally be achieved with the decreasing costs of wind power. Conversely, the maximum reduction in LCOS is 12% for "H_2, WE-Grid mix". The remaining options necessitate LCOS reductions within this spectrum, typically lower for ammonia than for hydrogen. Notably, the production cost of 1 kg of hydrogen is higher than that of producing 1 kg of ammonia (Dincer & Bicer, 2018). Additionally, transition to underground gas storage may facilitate cost reduction targets if it has the social and political acceptance in the desired region.

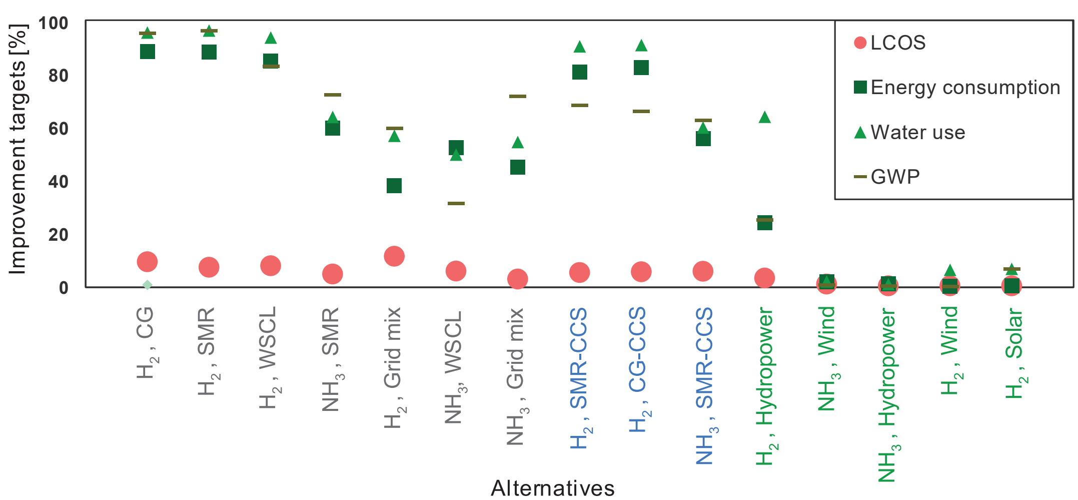

Figure 4: Improvement targets for long-term alternatives under uncertainty. The improvement target for each indicator and technology is estimated using the average of the 100 scenarios.

https://doi.org/10.52202/077185-0184

The most significant reduction required in electricity consumption is approximately 90%, primarily concerning grey and blue hydrogen, followed by WSCL (water splitting by chemical looping). Current pilot projects for Carbon Capture and Storage (CCS) systems consume substantial energy, yet ongoing technological advancements promise to reduce energy demands (X. Li et al., 2021). Conversely, for green hydrogen and ammonia, the required reduction in electricity consumption is modest, with "H_2, WE-Wind" needing only a 1% reduction, marking it the most favorable option among inefficient alternatives in this regard. Notably, heat waste occurs in gas production reactors (Ozturk & Dincer, 2021), and heat integration can further enhance performance. Regarding water usage, the pattern mirrors electricity consumption but with varying degrees, ranging from 1% for "NH_3, WE-Hydropower" to 97% for "H_2, SMR". Nearly all investigated long-term storage options require reductions in their GWP. Among inefficient DMUs, required changes begin below 1% for "H_2, WE-Wind" and escalate to 97% for "H_2, SMR". Implementing CCS, despite potentially worsening electricity consumption and LCOS, is crucial for controlling CO_2 emissions.

3.3 Effect of putting stress on environmental indicators

In this section, we delve into a theoretical case where an environmentally conscious stakeholder allocates 80% of the total weight to environmental considerations and the remaining 20% to other economic and social factors. We adopt a balanced approach within each sustainability dimension, distributing the weights equally among the indicators. Further details are discussed in section 2.4.

Figure 5 compares median performance scores achieved for each technology when 80% weight is allocated to environmental indicators (y-axis) with the median performance scores achieved when indicators are equally weighted (i.e., the median performance from the original DEA, x-axis). This figure is segmented into four quadrants, depending on the combination of efficient/inefficient status obtained in each analysis. Additionally, utilizing a diagonal line, technologies are categorized into two groups: those reporting higher performance when no predefined weights are assigned to indicators (located on the right side of the diagonal), and those benefiting from greater weights on environmental indicators (situated on the left side of the diagonal).

Assigning higher weights to environmental indicators leads to notable changes in the performance scores obtained by medium-term options. Technologies on the right side of the diagonal, namely NiCd, Li-ion, NaS, and Li-Fe-Ph, present decreases in performance from 1.61, 1.36, 1.32, and 1.03, respectively, to 1.05, 1.04, 1.03, 1.03, and 1. Nevertheless, all these technologies remain efficient in this analysis, revealing their robustness and solid environmental performance.

Conversely, technologies on the left side of the diagonal, such as Li-Ni-Mn-Co, Na-Ni-Cl, LA, ZBFB, and VRFB, benefit from increased weight on environmental indicators. They improve their median performance scores from 0.98, 0.4, 0.24, 0.07, and 0.03, respectively, to 1, 0.84, 0.81, 0.7, and 0.57. This improvement is sufficient for Li-Ni-Mn-Co to become efficient. However, despite enhancing their median performance scores, the rest remain inefficient, although with improved competitiveness against efficient technologies. The relative ranking of the technologies remains unaffected by increasing the weights of environmental indicators, indicating consistency with the analysis presented in section 3.1.

Shifting our focus to long-term energy storage alternatives, we represent them with ovals colored according to their category to maintain clarity in the figure. Located on the right side of the diagonal, green options such as hydrogen derived from water electrolysis fueled by solar ("H_2, WE-Solar") and wind energy ("H_2, WE-Wind"), as well as ammonia sourced from solar ("NH_3, WE-Solar"), wind ("NH_3, WE-Wind"), and hydropower ("NH_3, WE-Hydropower"), exhibit a decline in performance scores when greater emphasis is placed on environmental indicators. Indeed, allocating more weight to the environmental indicators results in a lower weight to employment indicators. Since these alternatives are efficient mainly because of their job creation opportunities, in turn, they report a decrease in their performance score. Despite this decline, these options maintain performance, underscoring their reliability for environmentally conscious applications.

 https://doi.org/10.52202/077185-0184

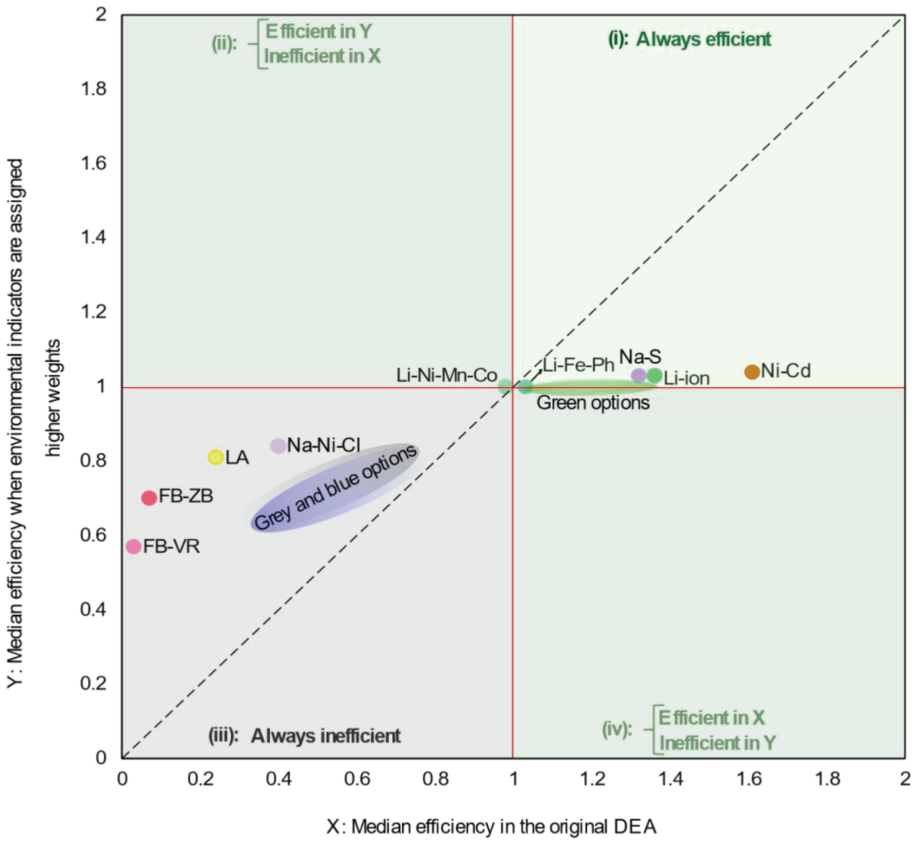

Figure 5: Median performance score obtained of medium-term and long-term energy storage options with and without predefined weights for the input and out indicators, under uncertainty.

Conversely, alternatives to the left of the diagonal experience an uptick in median performance compared to the original DEA results. This includes blue and grey options alongside power-to-hydrogen technologies utilizing water electrolysis powered by hydropower energy (“H_2, WE-Hydropower”). Note that since DEA is a relative comparison, an increase in performance of these alternatives is obtained because performance of green alternatives decreases in this analysis (i.e., employment indicator effect). Therefore, an improvement in their performance score does not mean that they are environmentally friendly choices. Furthermore, none achieves performance beyond one. Notably, like medium-term options, the variance between the highest and lowest median performance scores under unequal weighting is reduced (i.e., 1.02-0.73 vs. 1.26-0.23). In both analyses, “NH_3, WE-Solar” attains the highest median performance, while “H_2, CG” exhibits the lowest median score.

4 CONCLUSIONS

This study used data envelopment analysis to assess energy storage technologies, considering data uncertainty through 100 scenarios. NiCd emerged as the most efficient medium-term option, with a median performance score of 1.61, followed by NaS and Li-ion batteries suitable for electric vehicles. Conversely, VRFB and ZBFB were identified as the most inefficient, prompting the establishment of improvement targets for competitiveness. Among long-term alternatives, green options like hydrogen and ammonia from renewable sources demonstrated performance, while grey hydrogen from coal gasification and SMR processes proved inefficient. Despite the efficacy of green alternatives,

https://doi.org/10.52202/077185-0184

challenges persist in marketability and practical applications, necessitating comprehensive considerations beyond performance scores. Furthermore, efficient options identified in each cluster maintained their position by emphasizing attention to environmental indicators. These findings underscore the reliability of the evaluation and selected technologies to be used for energy storage. It is important to note that even inefficient options may have unique roles in specific applications/locations. Moreover, ongoing innovation in these technologies suggests potential for performance gains over time. Improvement targets highlight the need for reductions in indicators like LCOS and energy consumption, guiding developers in technology enhancement.

Researchers can leverage these findings to prioritize efforts aimed at enhancing the overall performance of each energy storage option. Further, policymakers are urged to incentivize the adoption of efficient technology and explore hybrid energy storage solutions to meet evolving energy needs effectively.

NOMENCLATURE

Λ	Intensity vector that reports the weight of each DMU	(–)
T^*	Performance of the DMU_o	(–)
m	Number of inputs	(–)
s_1	Number of desired outputs	(–)
s_2	Number of undesired outputs	(–)
S_i^-	Slack of inputs in the SBM model	(–)
S_r^g	Slack of desired outputs in the SBM model	(–)
Sr^b	Slack of undesired outputs in the SBM model	(–)
t	Charnes-Cooper linear transformation coefficient	(–)
x_{io}	Input i related to the DMU_O	(–)
X	Matrix of inputs	(–)
y_{ro}^g	Desired output r related to the DMU_O	(–)
y_{ro}^b	Undesired output r related to the DMU_O	(–)
Y^g	Matrix of desired outputs	(–)
Y^b	Matrix of undesired outputs	(–)

REFERENCES

Akram, U., Nadarajah, M., Shah, R., & Milano, F. (2020). A review on rapid responsive energy storage technologies for frequency regulation in modern power systems. Renewable and Sustainable Energy Reviews, 120, 109626. https://doi.org/https://doi.org/10.1016/j.rser.2019.109626

Barnosell, I., & Pozo, C. (2024). The impacts of the European chemical industry on the planetary boundaries. Sustainable Production and Consumption, https://doi.org/https://doi.org/10.1016/j.spc.2023.12.006

Blanco, H., & Faaij, A. (2018). A review at the role of storage in energy systems with a focus on Power to Gas and long-term storage. Renewable and Sustainable Energy Reviews, 81, 1049–1086. https://doi.org/https://doi.org/10.1016/j.rser.2017.07.062

Cabrera-Jiménez, R., Mateo-Sanz, J. M., Gavaldà, J., Jiménez, L., & Pozo, C. (2022). Comparing biofuels through the lens of sustainability: A data envelopment analysis approach. Applied Energy, 307, 118201. https://doi.org/https://doi.org/10.1016/j.apenergy.2021.118201

Chisalita, D.-A., Petrescu, L., & Cormos, C.-C. (2020). Environmental evaluation of european ammonia production considering various hydrogen supply chains. Renewable and Sustainable Energy Reviews, 130, 109964. https://doi.org/https://doi.org/10.1016/j.rser.2020.109964

Dincer, I., & Bicer, Y. (2018). 3.2 Ammonia Production. In I. Dincer (Ed.), Comprehensive Energy Systems (pp. 41–94). Elsevier. https://doi.org/https://doi.org/10.1016/B978-0-12-809597-3.00305-9

Fang, H.-H., Lee, H.-S., Hwang, S.-N., & Chung, C.-C. (2013). A slacks-based measure of super-efficiency in data envelopment analysis: An alternative approach. Omega, 41(4), 731–734. https://doi.org/https://doi.org/10.1016/j.omega.2012.10.004

https://doi.org/10.52202/077185-0184

Fernandez-Marchante, C. M., Millán, M., Medina-Santos, Jesús. I., & Lobato, J. (2020). Environmental and Preliminary Cost Assessments of Redox Flow Batteries for Renewable Energy Storage. Energy Technology, 8(11), 1900914. https://doi.org/https://doi.org/10.1002/ente.201900914

Frutiger, J., Jones, M., Ince, N. G., & Sin, G. (2018). From property uncertainties to process simulation uncertainties – Monte Carlo methods in SimSci PRO/II process simulator. In M. R. Eden, M. G. Ierapetritou, & G. P. Towler (Eds.), Computer Aided Chemical Engineering (Vol. 44, pp. 1489–1494). Elsevier. https://doi.org/https://doi.org/10.1016/B978-0-444-64241-7.50243-3

GIA. (2022). State of the art of energy storage regulations and technology. https://www.futured.es/wp-content/uploads/2016/06/GIA-Maqueta_eng.pdf

IRENA. (2020). Electricity Storage Valuation Framework: Assessing systems value and ensuring project viability.

Kumar, A., Ghosh, A., Ghosh, A., Ahuja, A., Sengupta, A., Forsyth, M., MacFarlane, D. R., & Mitra, S. (2021). Sub-zero and room-temperature sodium–sulfur battery cell operations: A rational current collector, catalyst and sulphur-host design and study. Energy Storage Materials, 42, 608–617. https://doi.org/https://doi.org/10.1016/j.ensm.2021.08.014

Li, H., Fang, K., Yang, W., Wang, D., & Hong, X. (2013). Regional environmental efficiency evaluation in China: Analysis based on the Super-SBM model with undesirable outputs. Mathematical and Computer Modelling, 58(5), 1018–1031. https://doi.org/https://doi.org/10.1016/j.mcm.2012.09.007

Li, X., Zhou, X., Wei, J., Fan, Y., Liao, L., & Wang, H. (2021). Reducing the energy penalty and corrosion of carbon dioxide capture using a novel nonaqueous monoethanolamine-based biphasic solvent. Separation and Purification Technology, 265, 118481. https://doi.org/https://doi.org/10.1016/j.seppur.2021.118481

Ming, J., Guo, J., Xia, C., Wang, W., & Alshareef, H. N. (2019). Zinc-ion batteries: Materials, mechanisms, and applications. Materials Science and Engineering,https://doi.org/https://doi.org/10.1016/j.mser.2018.10.002

Mostafa, M. H., Abdel Aleem, S. H. E., Ali, S. G., Ali, Z. M., & Abdelaziz, A. Y. (2020). Techno-economic assessment of energy storage systems using annualized life cycle cost of storage (LCCOS) and levelized cost of energy (LCOE) metrics. Journal of Energy Storage, 29, 101345. https://doi.org/https://doi.org/10.1016/j.est.2020.101345

Mukelabai, M. D., Gillard, J. M., & Patchigolla, K. (2021). A novel integration of a green power-to-ammonia to power system: Reversible solid oxide fuel cell for hydrogen and power production coupled with an ammonia synthesis unit. International Journal of Hydrogen Energy, 46(35), 18546–18556. https://doi.org/https://doi.org/10.1016/j.ijhydene.2021.02.218

Newborough, M., & Cooley, G. (2020). Developments in the global hydrogen market: Electrolyser deployment rationale and renewable hydrogen strategies and policies. Fuel Cells Bulletin, 2020(10), 16–22. https://doi.org/https://doi.org/10.1016/S1464-2859(20)30486-7

Ntavarinos, N., Davies, P., & Oterkus, E. (2019). Assessment of energy storage technologies for case studies with increased renewable energy penetration. Annals of Limnology and Oceanography, 4, 1–14.

Rostami, F., Kis, Z., Koppelaar, R., Jiménez, L., & Pozo, C. (2022). Comparative sustainability study of energy storage technologies using data envelopment analysis. Energy Storage Materials, 48, 412–438. https://doi.org/https://doi.org/10.1016/j.ensm.2022.03.026

Siddiqui, O., & Dincer, I. (2019). A well to pump life cycle environmental impact assessment of some hydrogen production routes. International Journal of Hydrogen Energy, 44(12), 5773–5786. https://doi.org/https://doi.org/10.1016/j.ijhydene.2019.01.118

The royal society. (2018). Options for producing low-carbon hydrogen at scale. https://royalsociety.org/-/media/policy/projects/hydrogen-production/energy-briefing-green-hydrogen.pdf

Thengane, S. K., Hoadley, A., Bhattacharya, S., Mitra, S., & Bandyopadhyay, S. (2014). Cost-benefit analysis of different hydrogen production technologies using AHP and Fuzzy AHP. International Journal of Hydrogen Energy, 39(28), 15293–15306. https://doi.org/10.1016/j.ijhydene.2014.07.107

Tone, K. (2011). Slacks-based measure of efficiency. Handbook on Data Envelopment Analysis, 195–209.

Van den Bossche, P., Vergels, F., Van Mierlo, J., Matheys, J., & Van Autenboer, W. (2006). SUBAT: An assessment of sustainable battery technology. Journal of Power Sources, 162(2), 913–919.

Zakeri, B., & Syri, S. (2015). Electrical energy storage systems: A comparative life cycle cost analysis. Renewable and Sustainable Energy Reviews, 42, 569–596. https://doi.org/https://doi.org/10.1016/j.rser.2014.10.011

Zhang, J., Zhang, G., Chen, Z., Dai, H., Hu, Q., Liao, S., & Sun, S. (2020). Emerging applications of atomic layer deposition for lithium-sulfur and sodium-sulfur batteries. Energy Storage Materials, 26, 513–533.

ACKNOWLEDGEMENT

The authors acknowledge the financial support from the Spanish Government (PID2021-127713OA-I00, PID2021-123511OB-C33, PID2021-124139NB-C22 & TED2021-129851B–I00).

https://doi.org/10.52202/077185-0184