https://doi.org/10.1016/j.est.2021.102808

Comparative Sustainability Efficiency Measurement of Energy Storages under Uncertainty: An Innovative Framework based on Interval SBM Model

Lin Ruojue[1], Yi Man[1], Carman K.M. Lee[1], Ping Ji[1], Ren Jingzheng[1*]

[1]Department of Industrial and Systems Engineering, Faulty of Engineering, The Hong Kong Polytechnic University, HKSAR, China

Corresponding author: Department of Industrial and Systems Engineering, The Hong Kong Polytechnic University, Hong Kong SAR, China

Email: jzhren@polyu.edu.hk; jire@iti.sdu.dk (J.Z. Ren)

Abstract

The variety of the energy storage materials and technologies leads to the selection difficulty. To evaluate the overall performance of energy storage technologies, this study proposed sustainability efficiency and sustainability super-efficiency indices. The proposed indices illustrate the integrated performance of energy storages in economic, environmental, technological and social aspects. A measurement framework was proposed based on data envelopment analysis models, the interval slacks-based measurement of efficiency and super efficiency. In this study, the concept of virtual DMUs is raised to solve the problem of instability of DEA due to insufficient DMUs analysed in the model. A case study is used to illustrate the proposed method and the

result has been analysed and validated. The Li-Ion battery is recognized as the most sustainable energy storage technologies among the four alternatives. This framework provides a feasible solution for prioritization of energy storage technologies while the number of alternatives is limited.

Keywords: Energy Storage; Sustainability; Sustainability Efficiency; Eco-efficiency; Data Envelopment Analysis; Uncertainty

1 Introduction

The development of modern power generation and power supply methods has spawned many new problems. Wind energy, solar energy, tidal energy, and other uncontrollable renewable energy power generation methods cause many waste wind and waste light to be generated. Various power generation methods cause the problem of instability of grid-connected current and voltage, and the power consumption time of the user has peak periods and other issues. These problems can be solved by installing electric energy storage devices. Therefore, the development of energy storage technology has become an important research direction of modern electric power.

Sustainability is an integrated and multi-dimensional concept. With the raising awareness of sustainability, the environmental, economic, technological and social aspects of energy storages have been assessed and analysed in recent studies. For example, Sternbeg and Bardow [1] examined the environmental sustainability of energy storage systems. Weber *et al.* [2] conducted the life cycle assessment for the Vanadium Redox Flow Battery. Davies *et al.* [3] evaluated the economic and technological aspect of battery energy storage for grid applications. Thomas *et al.* [4]discussed social acceptability of energy storage. However, the analysis in single aspect is insufficient to reflect the overall performance of energy storage. Therefore, the sustainability needs to be evaluated by considering multiple aspects of energy storages simultaneously. For instance, Yan *et al.* [5] evaluated energy storage in techno-economic and social aspects. Guo *et al.* [6] applied life cycle sustainability assessment to pumped hydro energy storage technology. Vo *et al.* [7] assess the environmental, economic and social sustainability of large-scale storage technologies.

Since the various energy storages have their own advantages and disadvantages, it is difficult for decision makers to choose the most suitable one. To solve this problem, comparative assessments are required. Many researchers have made the attempts. Because of their respective advantages, some scholars have proposed methods using MCDM to rank energy storage technologies. For example, Ren developed a method based on subjective judgment and can be used for uncertain intervals [8]. All studies corresponding to the selection of energy technologies based on sustainability are presented in **Table 1**.

Table 1. Literatures related to prioritization of energy storages

Topic	Indices	Ranking method	Ref.	Year
Energy storage technologies selection	Technical, economic, environmental and social	Hybrid trapezoidal neutrosophic fuzzy MAIRCA*	[9]	2020
Hydrogen energy storage technologies selection	Technical, and economic	Fuzzy AHP* and weighted fuzzy axiomatic design	[10]	2020
Energy storage technologies selection	Technical, economic, environmental, and social	Delphi, hesitant fuzzy AHP and VIKOR*	[11]	2020
Energy storage plans selection	Economic	Bayesian BWM*, entropy weighting method and grey cumulative prospect theory	[12]	2020
Electricity storage technologies selection	Technological, and economic	Fuzzy TOPSIS*	[13]	2020

Energy storage systems investigation	Technical, economic, environmental and social	Hesitant fuzzy AHP and hesitant fuzzy TOPSIS	[14]	2019
Energy storage technologies selection	Technical, economic, and environmental	Intuitionistic fuzzy MULTIMOORA*	[15]	2019
Battery energy storage systems ranking	Technical, economic, environmental, performance and social	Fuzzy Delphi method, BWM and fuzzy-cumulative prospect theory	[16]	2019
Battery energy storage systems selection	Technical, economic, and environmental	Augmented epsilon-constraint method	[17]	2019
Electricity storage technologies selection	Technological, economic, performance, and environmental	Non-linear fuzzy prioritization and IMADA*	[8]	2018
Electricity storage technologies selection	Technological, economic, and social	AHP	[18]	2016

Electricity storage technologies selection	Technical, economic, environmental and social	AHP and fuzzy TOPSIS	[19]	2015
Electricity storage technologies selection	Managemental, economic, and technical	Checklist	[20]	1999

* MAIRCA= Multi-Attributive Ideal-Real Comparative Analysis
* AHP=Analytical Hierarchy Process
* VIKOR=VIsekriterijumska Optimizcija I Kompromisno Resenje
* BWM=Best Worst Method
* TOPSIS=Technique for Order of Preference by Similarity to Ideal Solution
* MULTIMOORA= Multi-Objective Optimization on the basis of Ratio Analysis
* IMADA=Interval Multi-Attribute Decision Analysis

Among these studies, the values in multiple indices are integrated in each MCDM methods as a final score to prioritize the energy storage technologies. If the sustainability performance is integrated in the form of efficiency, the index is more instructive. The index eco-efficiency was then raised and widely used in sustainability evaluation [21–23] The eco-efficiency was also applied in the analysis for energy storage [24]. However, the economic benefit and environmental impact are the only two aspects considered in the eco-efficiency. To better illustrate sustainability, we propose a sustainability efficiency by considering environmental, economic, technological and social aspects.

Eco-efficiency was commonly measured and compared by Data Envelopment Analysis (DEA) methods [25–27]. DEA is a widely used method used to empirically measure productive efficiency of decision making units (DMUs). There are several DEA methods that could be used in different circumstances, such as CCR model [28] and BCC model [29]. Due to the effectiveness of the models, the DEA models have been widely applied in studies in different fields for efficiency calculation [30,31]. Then the DEA models have been used as ranking methods especially for those problems with multiple criteria [32]. Furthermore, the DEA models were adopted as the measurement of some extensive concept of efficiency, such as eco-efficiency. For example, Fan *et al.* [33] used BCC and CCR models to evaluate the eco-efficiency of industrial parks. In the new sustainability index, the DEA model can also be adopted. However, in reality, the uncertainty existing in the real cases when the indicators of sustainability were measured. To solve those problems, some extended DEA methods need to be proposed especially for the new sustainability indicator considering multiple aspects.

In a DEA model, the number of DMUs need to be more than 3 times of total amount of inputs and outputs and should be more than the number of inputs multiples the number of outputs, because insufficient amount of DMUs will lead to instability of efficient frontier and will further influence the result [34,35]. This requirement limits the application scope of the DEA model. To solve this problem, virtual DMUs are raised and applied in DEA models. For example, Shetty and Pakkala [36] proposed the single virtual inefficient DMU used in DEA. Ziari and Raissi [37] improved the DEA model with the help of virtual DMUs. Since the number of energy storage technologies are limited in case study, the virtual DMUs can be used in the proposed model to enable it being applied in comparison of small amount of DMUs.

As mentioned above, this article is aiming at filling following research gaps:

1) It lacks comparative sustainability analysis for energy storages providing comparative sustainability results of energy storages in economic, environmental, social and technological aspects.

2) An integrated sustainability index that can reflects the sustainability performance in economic, environmental, social and technological aspects is lack for sustainability analysis of energy storage technologies, which leads to difficulty in comparison of their sustainability performance.

3) It lacks stable prioritization methods to rank small number of alternatives for an index in production function while considering multiple criteria.

In order to fill the research gaps mentioned above, this paper adopts the improved DEA model that can be used for interval numbers to analyse the effectiveness of each energy storage alternatives and rank the sustainability of each energy storage alternatives.

Besides this section, section 2 introduces the definition of sustainability efficiency and sustainability super-efficiency; section 3 illustrates the detailed framework of sustainability efficiency measurement based on interval SBM and interval Super-SBM; a case with 4 energy storages technologies are studied in section 4; the results generated from case study are analysed in section 5; this proposed framework is evaluated by comparing with different traditional DEA methods and conducting sensitivity analysis in section 6; the section 7 concludes this study and the results.

2 Sustainability Efficiency and Sustainability Super-Efficiency

In order to more comprehensively and accurately evaluate and compare the sustainability of different energy storage solutions, the selection and unification of evaluation indices is very important. In the years of development, sustainability evaluation has expanded from only considering environmental factors to economic, environmental, and social aspects [38]. Among them, many scholars use three-pillar sustainability model, which includes environmental, economic and social aspects [39,40]. In addition to the above three indicators, some scholars also use technological, eco-technological, social-technological and other indicators [41].

In environmental aspect, the main consideration is the indicators related to human life. For example: land occupation area, air pollution, water pollution, etc. Environmental indicators are generally used as environmental indicators considered in original concept of sustainability. From economic perspective, profit, cost and investment index are the major categories. Indicators, such as capital cost, operation cost and maintenance cost, are usually used for cost measurement. Net profit, and productivity are frequently adapted for profit evaluation. Investment index are important indicators for decision makers to evaluate the value of investment. Therefore, some invest index, such as rate of return, deterioration rate, and net present value, will be included in the sustainable indices system as well. As for technological aspect, indicators related to the production performance of energy storage can be adopted to measure the sustainability. For example, lifespan, cycle life, technical maturity, scale, self-discharge rate, specific energy, energy density, specific power, and power density can be used as technological indicators. From social perspective, social acceptance and social benefit are commonly used in the sustainability evaluation. Since the social acceptance and social benefit are difficult to measure quantitatively, those indicators are usually expressed in linguistic term.

Summarized from literatures, the sustainable indicators for energy storage selection can be seen in **Table 2.**

Table 2. Sustainable indicators for energy storage selection

Aspect	Indices	Unit	Reference
Technological	Power	kW	[42–44]
	Capacity	kWh	[42,45,46]

	Energy conversion efficiency	%	[42,43,47,48]
	Energy density	kWh/m^3	[43,48–50]
	Lifetime	years	[49–52]
	Specific energy	$Wh\ kg^{-1}\ cycle^{-1}$	[43,44,53]
	Life Cycles	times	[46,50,52,53]
	Charging time	s	[54–56]
	Discharging time	s	[54,56,57]
	Energy ratio	\	[54]
	Power density	kW/I	[43,50,52,56]
	Maturity	\	[55,57,58]
	Self discharge rate	%/day	[55,56,59]
	Scale	MW	[43]
	Response time	s	[60,61]
	Charge rate	%	[56,60]
	Reliability	\	[62]
	Power rating	MW	[56,57]
	Operation temperature	℃	[56]
Economic	Utility energy cost	$/kWh	[42]
	Utility demand cost	$/kWh	[42]
	Utility fixed cost	$/kWh	[42]
	Net Present Value (NPV)	$	[42]
	Operation cost	$/kWh	[42,48,60]

	Maintenance cost	$/kWh	[42]
	Net CAPEX	$	[42]
	Capital cost	$/kWh	[42,43,48,49]
	Power installation cost	$	[52]
	Energy installation cost	$	[52]
	Investment cost	$/kWh	[50]
	Total cost	$/kWh	[61,62]
Social	Social acceptability	\	[48]
Environmental	CO_2 density	\	[48]
	Integrated environmental impact	\	[48,55,56]

To illustrate the multiple aspects of sustainability performances in one index, some integrated indices were raised. Among them, the concept of eco-efficiency, which can display the integrated performance of environmental and economic impacts, is widely used in sustainability evaluation. However, the sustainability includes not only the economic benefit and environmental impact, but also technological and social aspects.

In this study, a new integrated index called sustainability efficiency is proposed. The sustainability efficiency integrates environmental impact, economic cost, social impact and technological performance in an efficiency form as shown in **Fig.1**. The alternative is more sustainable when it has better technology performance and less impacts on environmental, economic and social aspects. Therefore, a sustainability efficiency is proposed to evaluate the sustainability by a production function. In this production function, environmental impact, economic cost, and social impact are the inputs and the technological performance is the output.

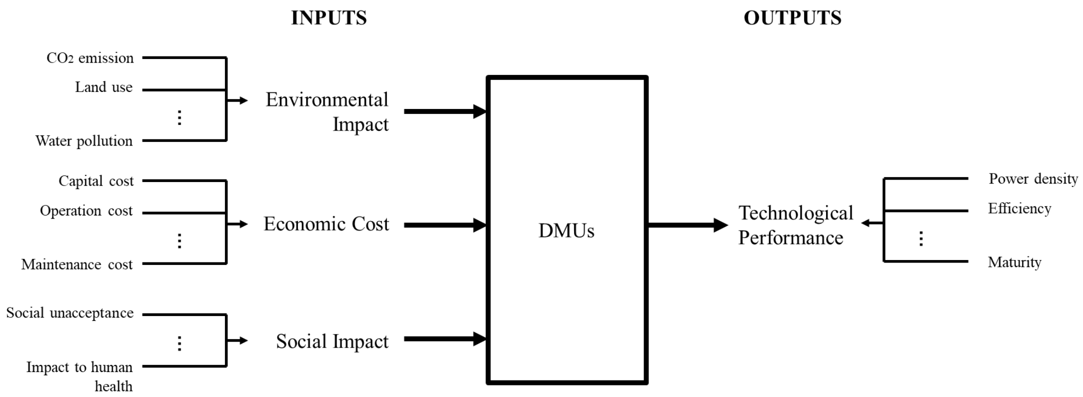

Fig.1 Model for sustainability efficiency

Each category index, such as environmental impact and economic cost, is an integrated value of multiple indices for this category index. For example, economic cost can be evaluated by indices such as capital cost and operation cost. The selection of indices for each category index can be screened according to the preference of decision makers and actual conditions. In this study, the selection of indices should fulfil following rules:

(1) The indices selected should not be overlapped or redundant. For example, maintenance cost is contained in operation cost, then the two indices cannot be selected simultaneously in one analysis.

(2) All indices selected as the sub-indices for economic cost, environmental impact, and social impact should be cost-type indices. The overall performance of the

DMU will be better, if the value of a cost-type index is smaller. For example, NPV is not a cost-type index, and the capital cost is suitable to be selected.

(3) All indices selected as the sub-indices for technological performance should be benefit-type indices. The overall performance of the DMU will be better, if the value of a benefit-type index is larger. For instance, the larger scale does not certainly mean the more sustainable performance of the DMU, because the energy storage technology with different scales is suitable for different application scenarios. Therefore, the scale is not an appropriate index selected.

The sustainability efficiency can be solved by using DEA models. The DMUs are efficient if their sustainability efficiency is 1. The DMUs are inefficient if sustainability efficiency is less than 1. By sequencing DMUs based on descending order, the DMUs can be prioritized for their sustainability performance. However, there might be more than one efficient DMUs, it might lead to failure in prioritization. Therefore, the sustainability super-efficiency, which is extended from super-efficiency, is proposed. Super-efficiency measures are widely utilized in DEA applications, especially for ranking the efficient DMUs. Similarly, the sustainability super-efficiency is proposed to measure the potentials of DMUs whose sustainability efficiency is 1.

3 Sustainability Efficiency Measurement Framework

In this study, a framework to determine the sustainability efficiency is proposed. The framework contains three main steps, which are DMUs determination, inputs and outputs determinations and sustainability efficiency determination as presented in **Fig.2**. In the first step, energy storage technologies are selected as DMUs. In the second step, the values of technological performance, environmental impact, economic cost and social impact of DMUs are determined by collecting data and normalization. The data of DMUs regarding to indices in environmental, economic, technological and social aspects can be collected by literature reviews, field trips and simulations. The last step is to determine the sustainability efficiency and sustainability super-efficiency by using interval SBM and interval Super-SBM respectively. The detailed steps are presented as below.

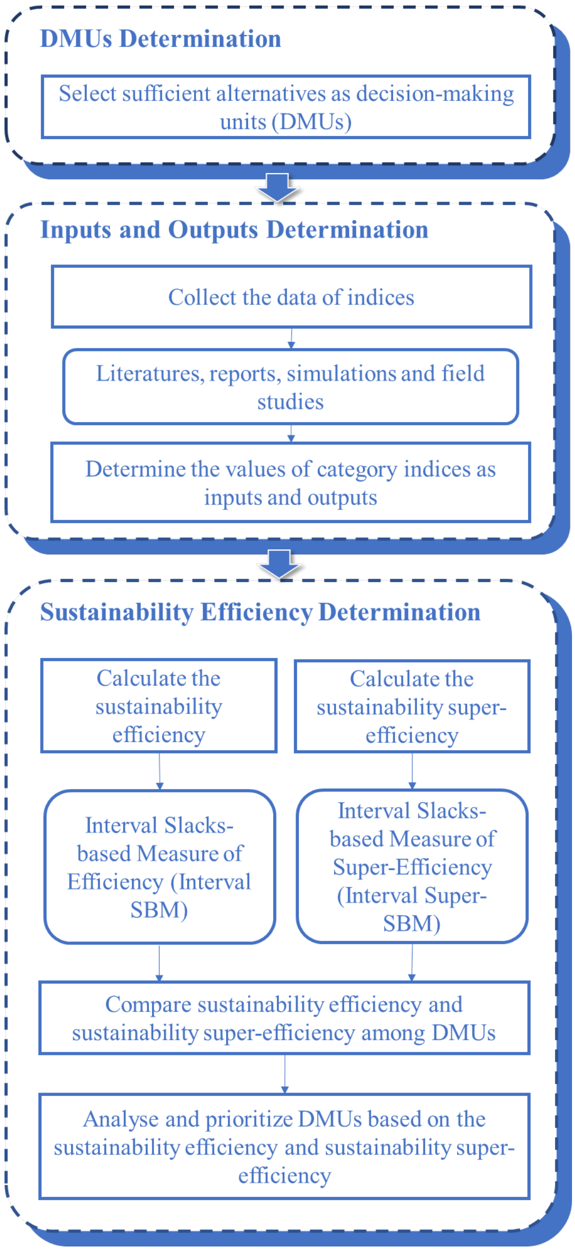

Fig.2 Research framework

Assume that n decision-making units (DMUs) are studied by analysing k_t indicators under technological performance as outputs, k_c indicators under economic cost as inputs, k_e indicators under environmental impact as inputs and k_s indicators under social impact as inputs.

3.1 DMUs Determination

The alternatives analysed are the DMUs in the DEA models. To maintain the stability of the DEA model, the number of DMUs should satisfy **Eqs.(1)-(2)** [34,35].

$$n \geq 3 \times (k_t + k_c + k_e + k_s) \quad (1)$$

$$n \geq k_t \times (k_c + k_e + k_s) \quad (2)$$

The limited number of DMUs leads to the instability of the model. To obtain a more accurate result, virtual DMUs are added to simulate sufficient number of DMUs with different sustainability performance. Therefore, if the number of DMUs analysed cannot satisfies the requirements, several virtual DMUs can be created to fulfil the requirement. The data values of virtual DMUs regarding all the inputs and outputs are determined by choosing random numbers within the scope of each input or output. The details of determination of the values of virtual DMUs can be referred to **Eqs.(3)-(6)** in session 3.2.

3.2 Inputs and Outputs Determination

The value of the *j*-th DMU with respect to the *i*-th indicator for technological performance is presented as $T_{ij} = \left[t_{ij}^L, t_{ij}^U\right], for\ i = 1,2, \dots, k_t$. Similarly, the values of the *j*-th DMU with respect to the *i*-th indicator for environmental impact, economic cost and social impact are presented as $E_{ij} = [e_{ij}^L, e_{ij}^U]$, $C_{ij} = [c_{ij}^L, c_{ij}^U]$, and $S_{ij} = [s_{ij}^L, s_{ij}^U]$ respectively (shown in **Table 3**).

Table 3. Hierarchical structure of indicators

Category	Indicators
Environmental Impact	$E_{1j} = [e_{1j}^L, e_{1j}^U]$
	$E_{2j} = [e_{2j}^L, e_{2j}^U]$
	…
	$E_{k_ej} = [e_{k_ej}^L, e_{k_ej}^U]$
Economic Cost	$C_{1j} = [c_{1j}^L, c_{1j}^U]$
	$C_{2j} = [c_{2j}^L, e_{2j}^U]$
	…
	$C_{k_cj} = [c_{k_cj}^L, c_{k_cj}^U]$
Social Impact	$S_{1j} = [s_{1j}^L, s_{1j}^U]$
	$S_{2j} = [s_{2j}^L, s_{2j}^U]$
	…
	$S_{k_sj} = [s_{k_sj}^L, s_{k_sj}^U]$
Technological Performance	$T_{1j} = [t_{1j}^L, t_{1j}^U]$
	$T_{2j} = [t_{2j}^L, t_{2j}^U]$
	…
	$T_{k_tj} = [t_{k_tj}^L, t_{k_tj}^U]$

The data of DMUs analysed with regard to the indicators can be collected for literature, report, simulation, field studies or investigation. In addition, the data of virtual DMUs should be determined by selecting random numbers within the range of those indicators. To be specific, the value of the virtual DMU v_0 regarding the i_0-th indicator under the category environmental impact can be determined by **Eq.(3)**.

$$e^L_{i_0 v_0} = e^U_{i_0 v_0} = \min_{j \notin V} e^L_{i_0 j} + \alpha(\max_{j \notin V} e^U_{i_0 j} - \min_{j \notin V} e^L_{i_0 j}) \quad (3)$$

where V is the set of virtual DMUs, and α is a random number and $\alpha \in [0,1]$. Similarly, the value of the virtual DMU v_0 regarding the i_0-th indicator under the category economic cost, social impact or technological performance can be determined by **Eqs.(4)-(6)**, respectively.

$$c^L_{i_0 v_0} = c^U_{i_0 v_0} = \min_{j \notin V} c^L_{i_0 j} + \alpha(\max_{j \notin V} c^U_{i_0 j} - \min_{j \notin V} c^L_{i_0 j}) \quad (4)$$

$$s^L_{i_0 v_0} = s^U_{i_0 v_0} = \min_{j \notin V} s^L_{i_0 j} + \alpha(\max_{j \notin V} s^U_{i_0 j} - \min_{j \notin V} s^L_{i_0 j}) \quad (5)$$

$$t^L_{i_0 v_0} = t^U_{i_0 v_0} = \min_{j \notin V} t^L_{i_0 j} + \alpha(\max_{j \notin V} t^U_{i_0 j} - \min_{j \notin V} t^L_{i_0 j}) \quad (6)$$

where V is the set of virtual DMUs; α is a random number and $\alpha \in [0,1]$.

In addition, as mentioned in the session 2, all indicators selected for economic cost, environmental impact, and social impact should be cost-type, and all indicators selected for technological performance should be benefit-type. If the i_0-th indicator under the category environmental impact, economic cost, social impact or technological performance selected does not satisfy this requirement, the original value for all DMUs regarding to this indicator $[\tilde{e}^L_{i_0 j}, \tilde{e}^U_{i_0 j}]$, $[\tilde{c}^L_{i_0 j}, \tilde{c}^U_{i_0 j}]$, $[\tilde{s}^L_{i_0 j}, \tilde{s}^U_{i_0 j}]$, or $[\tilde{t}^L_{i_0 j}, \tilde{t}^U_{i_0 j}]$ should be pre-treated by using **Eqs.(7)-(10)**, respectively.

$$[e^L_{i_0 j}, e^U_{i_0 j}] = [\max_{j \notin V} e^U_{i_0 j} - \tilde{e}^U_{i_0 j}, \max_{j \notin V} e^U_{i_0 j} - \tilde{e}^L_{i_0 j}], for\ j = 1,2, \ldots, n \quad (7)$$

$$[c^L_{i_0 j}, c^U_{i_0 j}] = [\max_{j \notin V} c^U_{i_0 j} - \tilde{c}^U_{i_0 j}, \max_{j \notin V} c^U_{i_0 j} - \tilde{c}^L_{i_0 j}], for\ j = 1,2, \ldots, n \quad (8)$$

$$\left[s_{i_0j}^L, s_{i_0j}^U\right] = [\max_{j \notin V} s_{i_0j}^U - \tilde{s}_{i_0j}^U, \max_{j \notin V} s_{i_0j}^U - \tilde{s}_{i_0j}^L], for\ j = 1,2,\dots,n \qquad (9)$$

$$\left[t_{i_0j}^L, t_{i_0j}^U\right] = [\max_{j \notin V} t_{i_0j}^U - \tilde{t}_{i_0j}^U, \max_{j \notin V} t_{i_0j}^U - \tilde{t}_{i_0j}^L], for\ j = 1,2,\dots,n \qquad (10)$$

3.3 Sustainability Efficiency Determination

Step 1. Determine the sustainability efficiency. The sustainability efficiency can be determined by using the interval SBM model [63]. Based on the definition of sustainability efficiency, the variables are revised accordingly. The sustainability efficiency $[\rho_{j_0}^L, \rho_{j_0}^U]$ of the j_0-th DMU can be determined by **Eqs.(11)-(12).**

$$\text{Min } \rho_{j_0}^L = \frac{1 - \frac{\sum_{i=1}^{k_e} \frac{\varepsilon_{ei}^-}{e_{ij_0}^U} + \sum_{i=1}^{k_c} \frac{\varepsilon_{ci}^-}{c_{ij_0}^U} + \sum_{i=1}^{k_s} \frac{\varepsilon_{si}^-}{s_{ij_0}^U}}{k_e + k_c + k_s}}{1 + \frac{\sum_{i=1}^{k_t} \frac{\varepsilon_{ti}^+}{t_{ij_0}^L}}{k_t}} \qquad (11)$$

Subject to

$$\begin{cases} t_{ij_0}^L = \sum_{j=1,\neq j_0}^{n} t_{ij}^U \lambda_j + t_{ij_0}^L \lambda_{j_0} - \varepsilon_{ti}^+, for\ \ i = 1,2,\dots,k_t \\ e_{ij_0}^U = \sum_{j=1,\neq j_0}^{n} e_{ij}^L \lambda_j + e_{ij_0}^U \lambda_{j_0} + \varepsilon_{ei}^-, for\ \ i = 1,2,\dots,k_e \\ c_{ij_0}^U = \sum_{j=1,\neq j_0}^{n} c_{ij}^L \lambda_j + c_{ij_0}^U \lambda_{j_0} + \varepsilon_{ci}^-, for\ \ i = 1,2,\dots,k_c \\ s_{ij_0}^U = \sum_{j=1,\neq j_0}^{n} s_{ij}^L \lambda_j + s_{ij_0}^U \lambda_{j_0} + \varepsilon_{si}^-, for\ \ i = 1,2,\dots,k_s \\ \lambda_j \geq 0, for\ j = 1,2,\dots,n \\ \varepsilon_{ti}^+ \geq 0, for\ \ i = 1,2,\dots,k_t \\ \varepsilon_{ei}^- \geq 0, for\ \ i = 1,2,\dots,k_e \\ \varepsilon_{ci}^- \geq 0, for\ \ i = 1,2,\dots,k_c \\ \varepsilon_{si}^- \geq 0, for\ \ i = 1,2,\dots,k_s \end{cases}$$

The solution $\rho_{j_0}^L$ indicates the lower bound of the sustainability efficiency for the j_0-

th DMU, when the equation is satisfied with the optimal solution.

$$\text{Min } \rho_{j_0}^{U} = \frac{1-\frac{\sum_{i=1}^{k_e}\frac{\varepsilon_{ei}^{-}}{e_{ij_0}^{L}}+\sum_{i=1}^{k_c}\frac{\varepsilon_{ci}^{-}}{c_{ij_0}^{L}}+\sum_{i=1}^{k_s}\frac{\varepsilon_{si}^{-}}{s_{ij_0}^{L}}}{k_e+k_c+k_s}}{1+\frac{\sum_{i=1}^{k_t}\frac{\varepsilon_{ti}^{+}}{t_{ij_0}^{U}}}{k_t}} \tag{12}$$

Subject to

$$\begin{cases} t_{ij_0}^{U} = \sum_{j=1,\neq j_0}^{n} t_{ij}^{L}\lambda_j + t_{ij_0}^{U}\lambda_{j_0} - \varepsilon_{ti}^{+}, for\ \ i = 1,2,\dots,k_t \\ e_{ij_0}^{L} = \sum_{j=1,\neq j_0}^{n} e_{ij}^{U}\lambda_j + e_{ij_0}^{L}\lambda_{j_0} + \varepsilon_{ei}^{-}, for\ \ i = 1,2,\dots,k_e \\ c_{ij_0}^{L} = \sum_{j=1,\neq j_0}^{n} c_{ij}^{U}\lambda_j + c_{ij_0}^{L}\lambda_{j_0} + \varepsilon_{ci}^{-}, for\ \ i = 1,2,\dots,k_c \\ s_{ij_0}^{L} = \sum_{j=1,\neq j_0}^{n} s_{ij}^{U}\lambda_j + s_{ij_0}^{L}\lambda_{j_0} + \varepsilon_{si}^{-}, for\ \ i = 1,2,\dots,k_s \\ \lambda_j \geq 0, for\ j = 1,2,\dots,n \\ \varepsilon_{ti}^{+} \geq 0, for\ \ i = 1,2,\dots,k_t \\ \varepsilon_{ei}^{-} \geq 0, for\ \ i = 1,2,\dots,k_e \\ \varepsilon_{ci}^{-} \geq 0, for\ \ i = 1,2,\dots,k_c \\ \varepsilon_{si}^{-} \geq 0, for\ \ i = 1,2,\dots,k_s \end{cases}$$

The solution $\rho_{j_0}^{U}$ indicates the upper bound of the sustainability efficiency for the j_0-th DMU, when the equation is satisfied with the optimal solution. If the upper bound of the sustainability efficiency $\rho_{j_0}^{U} = 1$, the j_0-th DMU is potential efficient DMU.

Step 2. Determine the sustainability super-efficiency. Due to the existence of more than one efficient DMUs in most cases, the sustainability super-efficiency is added to the model. The sustainability efficiency can be determined by using interval Super-SBM model [63]. The sustainability super-efficiency for the j_0-th DMU $[\tau_{j_0}^{L}, \tau_0^{U}]$ can be determined by **Eqs.(13)-(14)**.

$$\text{Min } \tau_{j_0}^{L} = \frac{\sum_{i=1}^{k_e}\frac{\tilde{e}_i^{U}}{e_{ij_0}^{U}}+\sum_{i=1}^{k_c}\frac{\tilde{c}_i^{U}}{c_{ij_0}^{U}}+\sum_{i=1}^{k_s}\frac{\tilde{s}_i^{U}}{s_{ij_0}^{U}}}{k_e+k_c+k_s} \tag{13}$$

Subject to

$$\begin{cases} \sum_{i=1}^{k_t} \frac{\tilde{t}_i^L}{t_{ij_0}^L} = 1, for \;\; i = 1,2,\dots,k_t \\ \tilde{e}_i^U \geq \sum_{j=1,\neq j_0}^{n} \alpha_j e_{ij}^L \,, for \;\; i = 1,2,\dots,k_e \\ \tilde{c}_i^U \geq \sum_{j=1,\neq j_0}^{n} \alpha_j c_{ij}^L \,, for \;\; i = 1,2,\dots,k_c \\ \tilde{s}_i^U \geq \sum_{j=1,\neq j_0}^{n} \alpha_j s_{ij}^L \,, for \;\; i = 1,2,\dots,k_s \\ \tilde{e}_i^U \geq \beta e_{ij_0}^U, for \;\; i = 1,2,\dots,k_e \\ \tilde{c}_i^U \geq \beta c_{ij_0}^U, for \;\; i = 1,2,\dots,k_c \\ \tilde{s}_i^U \geq \beta s_{ij_0}^U,, for \;\; i = 1,2,\dots,k_s \\ 0 \leq \tilde{t}_i^L \leq \beta t_{ij_0}^L, for \;\; i = 1,2,\dots,k_t \\ \lambda_j \geq 0, for\, j = 1,2,\dots,n \\ \beta > 0 \end{cases}$$

Min $\tau_{j_0}^U = \frac{\sum_{i=1}^{k_e} \frac{\tilde{e}_i^L}{e_{ij_0}^L} + \sum_{i=1}^{k_c} \frac{\tilde{c}_i^L}{c_{ij_0}^L} + \sum_{i=1}^{k_s} \frac{\tilde{s}_i^L}{s_{ij_0}^L}}{k_e + k_c + k_s}$ (14)

Subject to

$$\begin{cases} \sum_{i=1}^{k_t} \frac{\tilde{t}_i^U}{t_{ij_0}^U} = 1, for \;\; i = 1,2,\dots,k_t \\ \tilde{e}_i^L \geq \sum_{j=1,\neq j_0}^{n} \alpha_j e_{ij}^U \,, for \;\; i = 1,2,\dots,k_e \\ \tilde{c}_i^L \geq \sum_{j=1,\neq j_0}^{n} \alpha_j c_{ij}^U \,, for \;\; i = 1,2,\dots,k_c \\ \tilde{s}_i^L \geq \sum_{j=1,\neq j_0}^{n} \alpha_j s_{ij}^U \,, for \;\; i = 1,2,\dots,k_s \\ \tilde{e}_i^L \geq \beta e_{ij_0}^L, for \;\; i = 1,2,\dots,k_e \\ \tilde{c}_i^L \geq \beta c_{ij_0}^L, for \;\; i = 1,2,\dots,k_c \\ \tilde{s}_i^L \geq \beta s_{ij_0}^L,, for \;\; i = 1,2,\dots,k_s \\ 0 \leq \tilde{t}_i^U \leq \beta t_{ij_0}^U, for \;\; i = 1,2,\dots,k_t \\ \lambda_j \geq 0, for\, j = 1,2,\dots,n \\ \beta > 0 \end{cases}$$

The ranking of DMUs can be then determined by descending the value of the interval super-efficiency $[\tau_0^l, \tau_0^u]$ obtained from **Eqs.(13)-(14)** of efficient DMUs and interval efficiency generated from interval SBM model of inefficient DMUs.

Step 3. Classify DMUs. According to Xu et al.[63], the DMU can be classified into different categories based on the interval super-efficiency.

Class 1: Include all DMUs which are SBM super-efficient both in their best and worst situation as shown in **Eq.(15)**.

$$E^{++} = \{DMU_j, j \in N_n | \tau_j^l \geq 1\} \tag{15}$$

Class 2: Consists of all DMUs which are efficient in their best situation, but inefficient in their worst situation. The class was determined by **Eq.(16)**.

$$E^{+} = \{DMU_j, j \in N_n | \tau_j^l < 1 \ and \ \tau_j^u \geq 1\} \tag{16}$$

Class 3: Consists of all DMUs which are inefficient in their best situation. It goes without saying that such DMUs are, also, inefficient in their worst situation. This class can be determined by **Eq.(17)**.

$$E^{-} = \{DMU_j, j \in N_n | \ \tau_j^u < 1\} \tag{17}$$

Step 4. Rank the DMUs by descending order. The classification provides a recommendation references to decision maker, but the classification could not offer a strong sequence for all DMUs. Therefore, an order-relation-based interval comparison process is adapted to rank the DMUs based on super-efficiency generated from the interval super-SBM model. To compare two interval numbers $a = [a^l, a^u]$ and $b = [b^l, b^u]$, Sengupta and Pal [64] assume that $\frac{a^l + a^u}{2} \leq \frac{b^l + b^u}{2}$. Then the acceptability index of $a < b$ can be determined by **Eq.(18)**.

$$A(a < b) = \frac{(b^l + b^u) - (a^l + a^u)}{(b^u - b^l) + (a^u - a^l)} \tag{18}$$

If $A(a < b) = 0$, then $a < b$ is determined as unacceptable, and the ranking of a and b is $a \geq b$; if $0 < A(a < b) < 1$, then the acceptability index of $a < b$ is $A(a < b)$; and if $A(a < b) \geq 1$, then it is certain that $a < b$.

In this method, the ranking of DMU_0 could be determined by descending the number of positive $A\left(DMU_j < DMU_0\right)$, where $j = 1,2,\dots,n\ and\ j \neq 0$.Therefore, the DMUs can be ranked based on the score obtained by **Eqs.(13)-(14).** The ranking of DMU_0 could be determined by descending the number of positive $A\left(DMU_j < DMU_0\right)$, where $j \in N_n\ and\ j \neq 0$, based on the same interval comparison equations as shown above. If the interval S-SBM has no feasible solution, the DMUs can be ranked by sustainability efficiency generated from interval SBM model directly.

4 Case Study

A case is studied for sustainability efficiency analysis. Four typical energy storage technologies, including pumped hydroelectric storage (PHS), compressed-air energy storage (CAES), lead acid battery (Pb-Acid) and lithium-ion battery (Li-Ion) are discussed in the case study.

The PHS is a large-scale energy storage technology based on the transformation between the potential energy of water and the electricity power. The PHS owns the advantages including large capacity, mature technology, and high efficiency [65,66]. However, the requirement for building a PHS is high, as a PHS requires special condition for the location and land occupation [67,68]. The CAES system is built to storage energy by compressing air in a closed space. The great advantages of CAES include fast response speed, high energy density, high power density, low operation cost and low self-discharge rate [69,70]. However, two important factors limit the development of CAES. One is that the location selection of CAES is restricted by the geographical condition, and the other is that the capital cost is high [71,72]. Pb-Acid battery is mature battery technology with long invention period and large market. It is attractive to the market because of its low cost, low energy-to-weight ratio, a low energy-to-volume ratio, and a relatively large power-to-weight ratio [73,74]. But the raw material of the battery have potential negative impacts on the environment [74]. Li-Ion battery is another popular battery traded in the market. The advantages of the Li-Ion include long lifespan, light weight, high voltage, high energy density, low self-discharge rate and low cost [75,76]. But it is also limited by some safety concerns [77].

To evaluate the energy storage technologies, indicator system is built based on the requirements mentioned in the session 2 (see **Table 4**). The indicators, including efficiency, self-discharge rate, energy density and power density are evaluated for the category technological performance. As for economic cost, the indicators including capital cost, fixed cost, variable cost and replacement cost are considered. Under the category of environmental impact, there are indicators of ecosystems, resources, and global warming. As for the social impact, the indicators include reliability, safety and human health.

Table 4. Indicators for sustainability analysis

Category	Indicator	Type	Unit
Technological performance	Energy conversion efficiency	Benefit type	%
	Self discharge rate	Cost type	%
	Energy density	Benefit type	kWh/kg
	Power density	Benefit type	kW/kg
Economic cost	Capital cost	Cost type	€/kW
	Fixed cost	Cost type	€/kW
	Variable cost	Cost type	€/kW
	Replacement cost	Cost type	€/kW
Environmental impact	Ecosystems	Cost type	species.yr
	Resources	Cost type	$
	Global warming	Cost type	kg CO2-eq.
Social impact	Reliability	Benefit type	\
	Safety	Benefit type	\
	Human health	Cost type	DALY

Among all the indicators mentioned above, indicators for technological performance are set as outputs, and all the other indicators are set as inputs as presented in **Fig.3**.

Based on the nature of the indicators, the cost-type indicators include capital cost, fixed cost, variable cost, replacement cost, ecosystems, resources, global warming, human health and self-discharge rate. Meanwhile, the reliability, safety, efficiency, energy density and power density are benefit-type indicators.

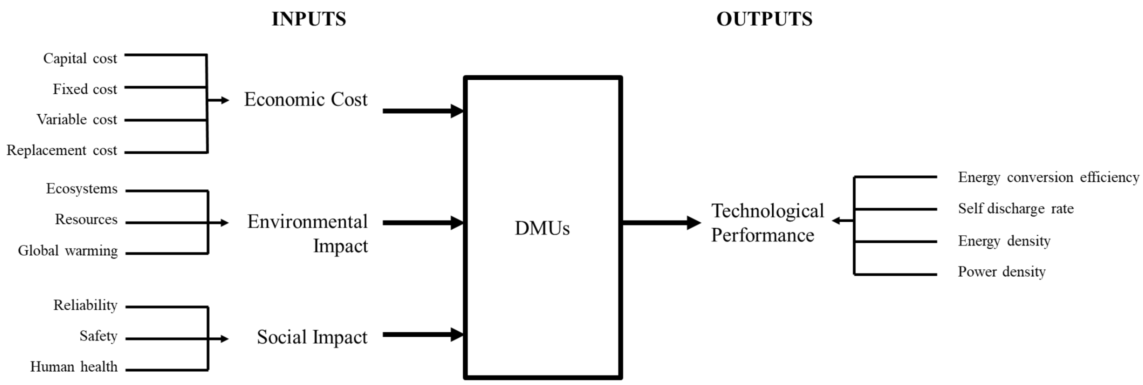

Fig.3 Inputs and outputs of DMUs

The values of PHS, CAES, Pb-Acid and Li-Ion regarding to the 14 indicators are collected based on literatures as presented in **Table 5**.

Table 5. Values of inputs and outputs

	PHS	**CAES**	**Pb-Acid**	**Li-Ion**	**Ref.**
Energy conversion efficiency	[65,87]	[40,89]	[63,90]	[70,100]	[78]
Self-discharge rate	0	0	[0.033,1.1]	[0.033,0.33]	[78]
Energy density	[0.5,1.5]	[0.4,20]	[25,90]	[94,500]	[78]
Power density	[0.00761,0.117]	[0.04,10]	[10,400]	[56.8,800]	[78]

Capital cost	51.3422	62.7644	56.3143	110.0533	[79]
Fixed cost	6.1246	5.1926	4.5269	9.1869	[79]
Variable cost	400.1564	598.5464	114.3304	88.9236	[79]
Replacement cost	0	0	235.338	220.2343	[79]
Ecosystems	0.0000034	0.00012	0.00032	0.00014	[80]
Resources	35	1100	750	180	[80]
Global warming	740	19000	31000	1900	[80]
Reliability	2	2	1	0	[4]
Safety	1	[0,1]	1	1	[4]
Human health	0.002	0.098	0.16	0.032	[80]

In this case study, 60 virtual DMUs are added to make the model more stable. The random number is generated by using '*rand()*' function in Microsoft Excel based on Mersenne Twister Generator [81]. The inputs and outputs data of the virtual DMUs are presented in **Appendix Table 1**. As shown in the **Fig.3**, the reliability, safety and self-discharge rate do not satisfy the requirements for data types of inputs and outputs. Therefore, the inputs and outputs data for this case study should be revised as **Table 6** determined by **Eq.(7)-(10)**.

Table 6. Revised inputs and outputs for the model

	PHS	CAES	Pb-Acid	Li-Ion
T_1	[65,87]	[40,89]	[63,90]	[70,100]

T_2	1.1	1.1	[0, 1.067]	[1.067,0.77]
T_3	[0.5,1.5]	[0.4,20]	[25,90]	[94,500]
T_4	[0.00761,0.117]	[0.04,10]	[10,400]	[56.8,800]
C_1	51.3422	62.7644	56.3143	110.0533
C_2	6.1246	5.1926	4.5269	9.1869
C_3	400.1564	598.5464	114.3304	88.9236
C_4	0	0	235.338	220.2343
E_1	0.0000034	0.00012	0.00032	0.00014
E_2	35	1100	750	180
E_3	740	19000	31000	1900
S_1	0	0	1	2
S_2	0	[0,1]	1	1
S_3	0.002	0.098	0.16	0.032

The values of the four energy storage technologies regarding to the 14 indicators are then evaluated by interval SBM model to calculate the sustainability efficiency based on **Eqs.(11)-(12)**. Taking PHS as an example, the sustainability efficiency can be determined by **Eqs.(19)-(20)**.

$$\text{Min } \rho_1^L = \frac{1-\frac{\sum_{i=1}^{3}\frac{\varepsilon_{ei}^-}{e_{i1}^U}+\sum_{i=1}^{4}\frac{\varepsilon_{ci}^-}{c_{i1}^U}+\sum_{i=1}^{3}\frac{\varepsilon_{si}^-}{s_{i1}^U}}{10}}{1+\frac{\sum_{i=1}^{4}\frac{\varepsilon_{ti}^+}{t_{i1}^L}}{4}} \tag{19}$$

Subject to

$$
\begin{cases}
t_{i1}^{L} = \sum_{j=2}^{64} t_{ij}^{U}\lambda_j + t_{i1}^{L}\lambda_1 - \varepsilon_{ti}^{+}, for\ \ i = 1,2,3,4 \\
e_{i1}^{U} = \sum_{j=2}^{64} e_{ij}^{L}\lambda_j + e_{i1}^{U}\lambda_1 + \varepsilon_{ei}^{-}, for\ \ i = 1,2,3 \\
c_{i1}^{U} = \sum_{j=2}^{64} c_{ij}^{L}\lambda_j + c_{i1}^{U}\lambda_1 + \varepsilon_{ci}^{-}, for\ \ i = 1,2,3,4 \\
s_{i1}^{U} = \sum_{j=2}^{64} s_{ij}^{L}\lambda_j + s_{i1}^{U}\lambda_1 + \varepsilon_{si}^{-}, for\ \ i = 1,2,3 \\
\lambda_j \geq 0, for\ j = 1,2,\ldots,64 \\
\varepsilon_{ti}^{+} \geq 0, for\ \ i = 1,2,3,4 \\
\varepsilon_{ei}^{-} \geq 0, for\ \ i = 1,2,3 \\
\varepsilon_{ci}^{-} \geq 0, for\ \ i = 1,2,3,4 \\
\varepsilon_{si}^{-} \geq 0, for\ \ i = 1,2,3
\end{cases}
$$

Min $\rho_1^U = \dfrac{1 - \dfrac{\sum_{i=1}^{3}\frac{\varepsilon_{ei}^{-}}{e_{i1}^{L}} + \sum_{i=1}^{4}\frac{\varepsilon_{ci}^{-}}{c_{i1}^{L}} + \sum_{i=1}^{3}\frac{\varepsilon_{si}^{-}}{s_{i1}^{L}}}{10}}{1 + \dfrac{\sum_{i=1}^{4}\frac{\varepsilon_{ti}^{+}}{t_{i1}^{U}}}{4}}$ (20)

Subject to

$$
\begin{cases}
t_{i1}^{U} = \sum_{j=2}^{64} t_{ij}^{L}\lambda_j + t_{i1}^{U}\lambda_1 - \varepsilon_{ti}^{+}, for\ \ i = 1,2,3,4 \\
e_{i1}^{L} = \sum_{j=2}^{64} e_{ij}^{U}\lambda_j + e_{i1}^{L}\lambda_1 + \varepsilon_{ei}^{-}, for\ \ i = 1,2,3 \\
c_{i1}^{L} = \sum_{j=2}^{64} c_{ij}^{U}\lambda_j + c_{i1}^{L}\lambda_1 + \varepsilon_{ci}^{-}, for\ \ i = 1,2,3,4 \\
s_{i1}^{L} = \sum_{j=2}^{64} s_{ij}^{U}\lambda_j + s_{i1}^{L}\lambda_1 + \varepsilon_{si}^{-}, for\ \ i = 1,2,3 \\
\lambda_j \geq 0, for\ j = 1,2,\ldots,64 \\
\varepsilon_{ti}^{+} \geq 0, for\ \ i = 1,2,3,4 \\
\varepsilon_{ei}^{-} \geq 0, for\ \ i = 1,2,3 \\
\varepsilon_{ci}^{-} \geq 0, for\ \ i = 1,2,3,4 \\
\varepsilon_{si}^{-} \geq 0, for\ \ i = 1,2,3
\end{cases}
$$

Therefore, solutions for **Eqs.(19)-(20)** are the lower boundary and the upper boundary of the sustainability efficiency. Similarly, the sustainability efficiency for CAES, Pb-Acid and Li-Ion can be determined, and the results are presented in **Table 7**.

Then, the values of the four energy storage technologies regarding to the 14 indicators presented in the **Table 6** can be used to determine the sustainability super-efficiency based on **Eqs.(13)-(14)**. Taking PHS as an example, the sustainability super-efficiency can be determined by **Eqs.(21)-(22).**

$$\text{Min } \tau_1^L = \frac{\sum_{i=1}^{3}\frac{\tilde{e}_i^U}{e_{i1}^U}+\sum_{i=1}^{4}\frac{\tilde{c}_i^U}{c_{i1}^U}+\sum_{i=1}^{3}\frac{\tilde{s}_i^U}{s_{i1}^U}}{10} \tag{21}$$

Subject to

$$\begin{cases} \sum_{i=1}^{4}\frac{\tilde{t}_i^L}{t_{i1}^L} = 1, for\ \ i = 1,2,3,4 \\ \tilde{e}_i^U \geq \sum_{j=2}^{64} \alpha_j e_{ij}^L\, , for\ \ i = 1,2,\ldots,k_e \\ \tilde{c}_i^U \geq \sum_{j=2}^{64} \alpha_j c_{ij}^L\, , for\ \ i = 1,2,\ldots,k_c \\ \tilde{s}_i^U \geq \sum_{j=2}^{64} \alpha_j s_{ij}^L\, , for\ \ i = 1,2,\ldots,k_s \\ \tilde{e}_i^U \geq \beta e_{i1}^U, for\ \ i = 1,2,3 \\ \tilde{c}_i^U \geq \beta c_{i1}^U, for\ \ i = 1,2,3,4 \\ \tilde{s}_i^U \geq \beta s_{i1}^U,, for\ \ i = 1,2,3 \\ 0 \leq \tilde{t}_i^L \leq \beta t_{i1}^L, for\ \ i = 1,2,3,4 \\ \lambda_j \geq 0, for\, j = 1,2,\ldots,64 \\ \beta > 0 \end{cases}$$

$$\text{Min } \tau_1^U = \frac{\sum_{i=1}^{3}\frac{\tilde{e}_i^L}{e_{i1}^L}+\sum_{i=1}^{4}\frac{\tilde{c}_i^L}{c_{i1}^L}+\sum_{i=1}^{3}\frac{\tilde{s}_i^L}{s_{i1}^L}}{10} \tag{22}$$

Subject to

$$
\begin{cases}
\sum_{i=1}^{4} \frac{\tilde{t}_i^U}{t_{i1}^U} = 1, for \;\; i = 1,2,3,4 \\
\tilde{e}_i^L \geq \sum_{j=2}^{64} \alpha_j e_{ij}^U \, , for \;\; i = 1,2,3 \\
\tilde{c}_i^L \geq \sum_{j=2}^{64} \alpha_j c_{ij}^U \, , for \;\; i = 1,2,3,4 \\
\tilde{s}_i^L \geq \sum_{j=2}^{64} \alpha_j s_{ij}^U \, , for \;\; i = 1,2,3 \\
\tilde{e}_i^L \geq \beta e_{i1}^L, for \;\; i = 1,2,3 \\
\tilde{c}_i^L \geq \beta c_{i1}^L, for \;\; i = 1,2,3,4 \\
\tilde{s}_i^L \geq \beta s_{i1}^L,, for \;\; i = 1,2,3 \\
0 \leq \tilde{t}_i^U \leq \beta t_{i1}^U, for \;\; i = 1,2,3,4 \\
\lambda_j \geq 0, for\, j = 1,2, \ldots ,64 \\
\beta > 0
\end{cases}
$$

The lower boundary and the upper boundary of the sustainability super-efficiency for PHS can be then determined by solving equations above respectively. Similarly, the sustainability super-efficiency can be determined by **Eqs.(13)-(14)** and the results are presented in **Table 7**. Based on **Eqs.(15)-(17)**, PHS, CAES, Pb-Acid and Li-Ion can be classified as “E++”, “E++”, “E+” and “E++”, respectively. It’s obvious that energy storage technologies cannot be ranked based on the classification. The ranking method presented in **Eq.(18)** is applied to determine the rank of energy storage technologies based on their sustainability efficiency and sustainability super-efficiency.

Table 7 Sustainability efficiency and sustainability super-efficiency of energy storage technologies

	Sustainability Efficiency		Sustainability Super-Efficiency		
DMU	**Score**	**Rank**	**Score**	**Class**	**Rank**
PHS	[1,1]	1st	[1.885,1.916]	E++	2nd
CAES	[1,1]	1st	[1,1.024]	E++	3rd
Pb-Acid	[0.010,1]	4th	[0.010,1.236]	E+	4th
Li-Ion	[1,1]	1st	[1.454,2.776]	E++	1st

5 Result and Discussion

In this section, the sustainability efficiency measurement and ranking results are illustrated and analysed.

5.1 Result illustration

According to **Table 7**, PHS, CAES and Li-Ion are efficient DMUs because their sustainability efficiencies are equal to 1, which means they are in the frontier of the DEA model. The Pb-Acid battery is the only DMU that is inefficient in this case study. Based on the sustainability efficiency, PHS, CAES and Li-Ion can be recognized as the sustainability-efficient options, while Pb-Acid is the sustainability-inefficient option. The three sustainability-efficient options are more recommended to be applied in different scenarios as energy storage options, comparing with Pb-Acid.

However, if energy storage options need to be prioritized to select the most sustainable option, the sustainability efficiency is not a criterion to sufficiently prioritize the energy storage technologies. Comparing with the sustainability super-efficiencies of energy storage technologies, the sustainability efficiencies of different energy storage technologies are almost indifferent. Therefore, the sustainability super-efficiency can be regarded as the criterion to prioritize the four energy storage technologies.

The result of sustainability super-efficiency illustrates that Li-Ion battery is the most sustainability-efficient option among all the options. The PHS ranks the second, and the CAES is the third sustainable one. As same as illustrated by the sustainability efficiency, the Pb-Acid battery is the less sustainability-efficient one.

According to **Table 5**, Li-Ion battery performs better than the other energy storage options in efficiency, energy density, power density and variable cost. Its technological performance is obviously the best one. The economic cost, environmental impact and social impact of Li-Ion battery are higher than some of other options, but Li-Ion battery are not the worst one in economic, environment and social aspects. Overall speaking, the Li-Icon battery can be the best among four energy storage in sustainability. Comparing the PHS and CAES, the PHS is more sustainable than the CAES in most criteria. Those advantageous criteria are efficiency, capital cost, variable cost, ecosystems, resources, global warming, and human health. The Pb-Acid battery is obvious the less sustainable one, because the Pb-Acid battery is worst in several indicators, such as self-discharge rate, replacement cost, ecosystems, global warming, reliability, safety and human health. Therefore, the rank based on the sustainability super-efficiency is feasible.

5.2 Evaluation for sustainability efficiency and sustainability super-efficiency

The ranking results of sustainability efficiency and sustainability super-efficiency are quite different. Because all alternatives have the potential to be the most sustainable one, the ranking of the energy storages are based on the minimum values of sustainability efficiency. However, the worst performance cannot be regarded as the only consideration in the sustainability analysis. Therefore, in this case study, the result of sustainability super-efficiency is more preferred, as it considered the advanced potential of each energy storage technology in sustainability aspect.

As shown in **Table 7**, more than one energy storages are classified as “E++”, which makes them indifferent. Therefore, the comparison between interval numbers added to the methodology for ranking is significant to prioritize the alternatives. Therefore, the interval Super-SBM is more suitable method to be used as the method for sustainability super-efficiency.

5.3 Sensitivity Analysis

To evaluate the robustness of the modelling result with virtual DMUs, more cases with different number of virtual DMUs are studied. The details of each run of case study are presented as below.

Table 8. Dataset in different scenarios

	No. of Virtual DMUs		
No. of runs	**60Virtual DMUs**	**40 Virtual DMUs**	**20 Virtual DMUs**
D1	Appendix Table 1	Appendix Table 11	Appendix Table 21
D2	Appendix Table 2	Appendix Table 12	Appendix Table 22
D3	Appendix Table 3	Appendix Table 13	Appendix Table 23
D4	Appendix Table 4	Appendix Table 14	Appendix Table 24
D5	Appendix Table 5	Appendix Table 15	Appendix Table 25
D6	Appendix Table 6	Appendix Table 16	Appendix Table 26

D7	Appendix Table 7	Appendix Table 17	Appendix Table 27
D8	Appendix Table 8	Appendix Table 18	Appendix Table 28
D9	Appendix Table 9	Appendix Table 19	Appendix Table 29
D10	Appendix Table 10	Appendix Table 20	Appendix Table 30

The results of each run of evaluation are presented in **Figs.4-6**. **Fig. 4** refers to sustainability super-efficiencies for energy storage technologies in each run (D1-D10) by using 60 virtual DMUs. **Fig. 5** refers to sustainability super-efficiencies for energy storage technologies in each run (D1-D10) by using 40 virtual DMUs. **Fig. 6** refers to sustainability super-efficiencies for energy storage technologies in each run (D1-D10) by using 20 virtual DMUs.

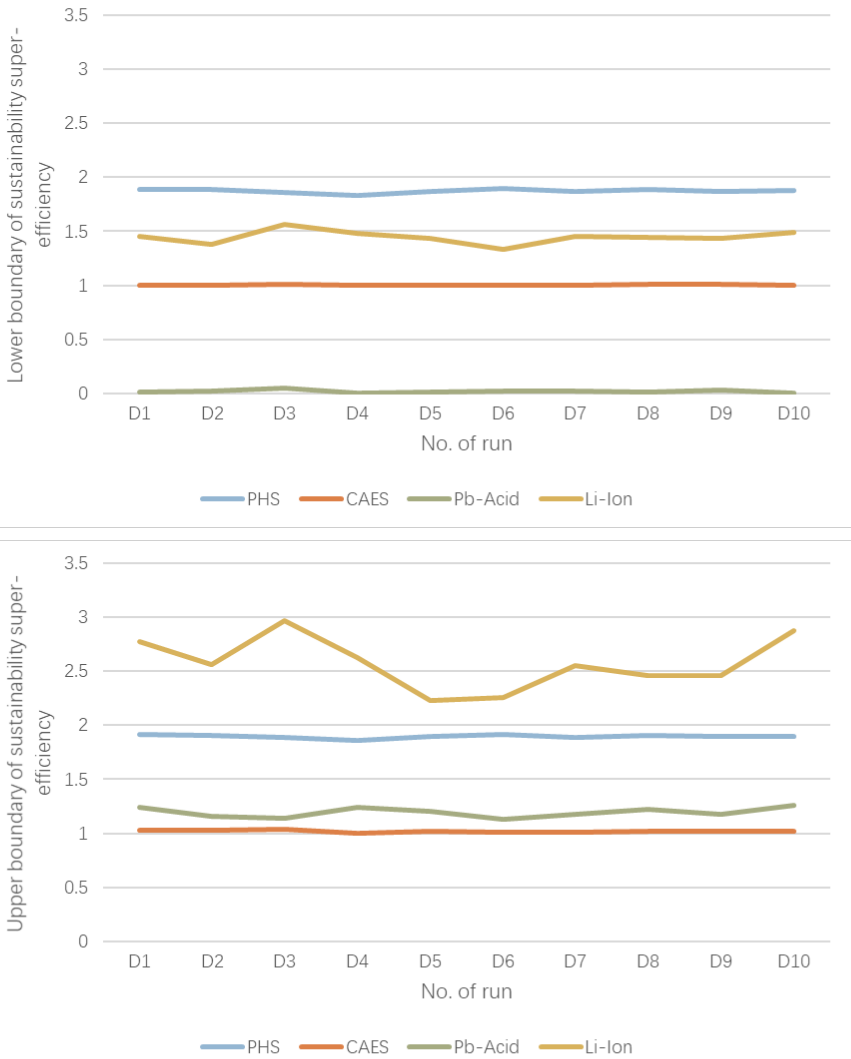

Fig.4 Sustainability super-efficiencies for energy storage technologies by using 60 virtual DMUs

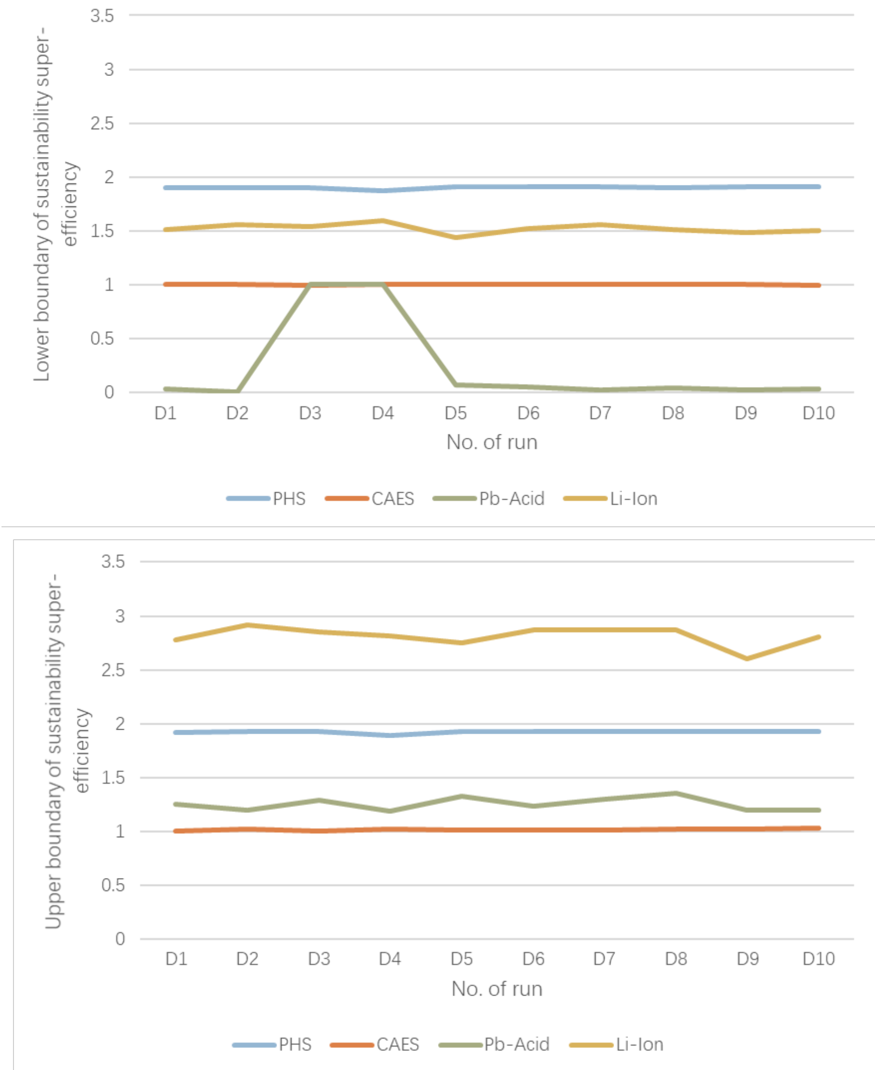

Fig.5 Sustainability super-efficiencies for energy storage technologies by using 40 virtual DMUs

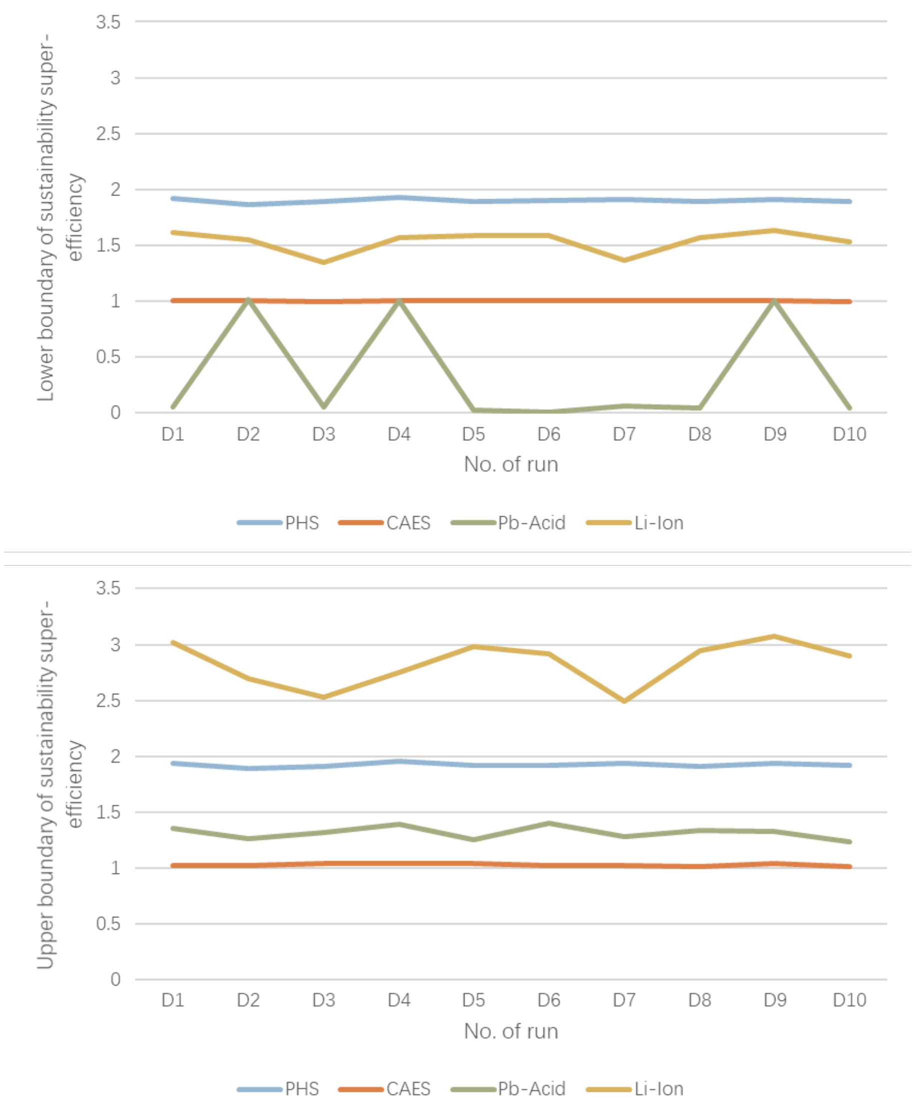

Fig.6 Sustainability super-efficiencies for energy storage technologies by using 20 virtual DMUs

According to **Figs.4-6**, the more virtual DMUs used in the modelling, the scores for each DMU in different run are more consistent. It indicates that the more virtual DMUs adopted in the model, the more stable the result of the sustainability super-efficiency is. As presented in **Fig.4**, the sustainability super-efficiency of each energy storage alternative is relatively consistent and stable. Therefore, the requirements presented in **Eqs.(1)-(2)** are sufficient to determine the number of virtual DMUs used in the model.

The rank for all the runs is the same. It's proven that the DEA model with virtual DMUs is feasible and the result is robust.

5.4 Comparison with other MCDM methods

To illustrate the differences between proposed prioritization model and the classical MCDM models, the interval TOPSIS [82] and the interval VIKOR [83] are chosen to prioritize the same case. The weights of indicators are determined by using classical weighting method AHP [84]. The calculation processes of two evaluation methods are presented in **Appendix Part II** and the results are presented in **Table 9**.

Table 9. Rank of energy storage technologies determined by different methods

	Sustainability Efficiency	Sustainability Super-Efficiency	AHP + Interval TOPSIS	AHP + Interval VIKOR
PHS	1st	2nd	2nd	2nd
CAES	1st	3rd	3rd	3rd
Pb-Acid	4th	4th	4th	4th
Li-Ion	1st	1st	1st	1st

It's shown that the ranking results of two MCDM methods and sustainability super-efficiency are consistent, which means the result of the ranking of sustainability super-efficiency is feasible and reliable. Comparing the proposal method with traditional DEA models and classical MCDM models in following aspects, the proposed method performs better in following aspects.

1) The MCDM models used for solving prioritization problem usually contain a step to determine the weights of criteria. In proposed method, a DEA model is used for ranking alternatives which does not require weights of criteria.

2) The traditional DEA model requires more DMUs to make the model stable. In a multi-criteria prioritization problem, data for multiple criteria are difficult to collect. In this case, the virtual DMUs helps to make the model stable and save the time for researchers to collect more data for DMUs which are not considered in the case study.

Therefore, the proposed method is an option to reduce the ranking process, while can reduce the inaccuracy caused by the subjective judgement adopted in the determination process of weights of indicators. In this case, the prioritization framework based on sustainability super-efficiency concept and interval S-SBM model is less time-consuming and can provide a more objective ranking result.

6 Conclusions

In this study, the sustainability efficiency and the sustainability super-efficiency were proposed as two integrated indices for sustainability evaluation. The interval slacks-based measurement of efficiency and super-efficiency were revised to measure the sustainability efficiency and super-efficiency. A case for sustainability evaluation and prioritization of energy technologies were then studied by using the proposed method. The results of the case study were analysed, and the proposed method was compared with other DEA methods. The results illustrate that the sustainability efficiency and sustainability super-efficiency can display overall sustainability performance in all environmental, economic, technological and social aspect. In addition, comparing to other DEA methods, the revised interval Super-SBM provide a more accurate result while considering the uncertainty existing in data.

This framework provides a feasible solution for prioritization of energy storage technologies while the number of alternatives is limited. The sustainability efficiency and sustainability super-efficiency are integrated indices to reflect the sustainability performance of energy storage technologies. It’s also a good reference for battery engineers to consider as the one of selection criteria for battery selection. In addition, this study can also provide a reference for policy makers. The Li-Ion battery is recognized as the most sustainable energy storage technologies among the four alternatives. However, the installed capacity of Li-Ion battery as the large-scale energy storage facility is not more than that of other energy storage technologies in China. The research and development of Li-Ion battery should be encouraged, and application of this battery can be further discovered.

The work described in this paper was supported by the grant from the Research Committee of The Hong Kong Polytechnic University under student account code RK22 and was also financially supported by The Postdoctoral Fellowships Scheme (G-YW4Y).

References

[1] A. Sternberg, A. Bardow, Power-to-What?-Environmental assessment of energy storage systems, Energy Environ. Sci. (2015). https://doi.org/10.1039/c4ee03051f.

[2] S. Weber, J.F. Peters, M. Baumann, M. Weil, Life Cycle Assessment of a Vanadium Redox Flow Battery, Environ. Sci. Technol. (2018). https://doi.org/10.1021/acs.est.8b02073.

[3] D.M. Davies, M.G. Verde, O. Mnyshenko, Y.R. Chen, R. Rajeev, Y.S. Meng, G. Elliott, Combined economic and technological evaluation of battery energy storage for grid applications, Nat. Energy. (2019). https://doi.org/10.1038/s41560-018-0290-1.

[4] G. Thomas, C. Demski, N. Pidgeon, Deliberating the social acceptability of energy storage in the UK, Energy Policy. (2019). https://doi.org/10.1016/j.enpol.2019.110908.

[5] X. Yan, X. Zhang, H. Chen, Y. Xu, C. Tan, Techno-economic and social analysis of energy storage for commercial buildings, Energy Convers. Manag. (2014). https://doi.org/10.1016/j.enconman.2013.10.014.

[6] Z. Guo, S. Ge, X. Yao, H. Li, X. Li, Life cycle sustainability assessment of pumped hydro energy storage, Int. J. Energy Res. (2020). https://doi.org/10.1002/er.4890.

[7] T.T.Q. Vo, A. Xia, F. Rogan, D.M. Wall, J.D. Murphy, Sustainability assessment

of large-scale storage technologies for surplus electricity using group multi-criteria decision analysis, Clean Technol. Environ. Policy. (2017). https://doi.org/10.1007/s10098-016-1250-8.

[8] J. Ren, X. Ren, Sustainability ranking of energy storage technologies under uncertainties, J. Clean. Prod. 170 (2018) 1387–1398. https://doi.org/10.1016/j.jclepro.2017.09.229.

[9] D. Pamucar, M. Deveci, D. Schitea, L. Erişkin, M. Iordache, I. Iordache, Developing a novel fuzzy neutrosophic numbers based decision making analysis for prioritizing the energy storage technologies, Int. J. Hydrogen Energy. (2020). https://doi.org/10.1016/j.ijhydene.2020.06.016.

[10] M. Karatas, Hydrogen energy storage method selection using fuzzy axiomatic design and analytic hierarchy process, Int. J. Hydrogen Energy. (2020). https://doi.org/10.1016/j.ijhydene.2019.11.130.

[11] M. Çolak, İ. Kaya, Multi-criteria evaluation of energy storage technologies based on hesitant fuzzy information: A case study for Turkey, J. Energy Storage. (2020). https://doi.org/10.1016/j.est.2020.101211.

[12] N. Li, H. Zhang, X. Zhang, X. Ma, S. Guo, How to select the optimal electrochemical energy storage planning program? a hybridmcdmmethod, Energies. 13 (2020) 1–20. https://doi.org/10.3390/en13040931.

[13] A.K.S. Maisanam, A. Biswas, K.K. Sharma, An innovative framework for electrical energy storage system selection for remote area electrification with renewable energy system: Case of a remote village in India, J. Renew. Sustain.

Energy. (2020). https://doi.org/10.1063/1.5126690.

[14] C. Acar, A. Beskese, G.T. Temur, A novel multicriteria sustainability investigation of energy storage systems, Int. J. Energy Res. (2019). https://doi.org/10.1002/er.4459.

[15] C. Zhang, C. Chen, D. Streimikiene, T. Balezentis, Intuitionistic fuzzy MULTIMOORA approach for multi-criteria assessment of the energy storage technologies, Appl. Soft Comput. J. (2019). https://doi.org/10.1016/j.asoc.2019.04.008.

[16] H. Zhao, S. Guo, H. Zhao, Comprehensive assessment for battery energy storage systems based on fuzzy-MCDM considering risk preferences, Energy. (2019). https://doi.org/10.1016/j.energy.2018.11.129.

[17] L. Li, P. Liu, Z. Li, X. Wang, A multi-objective optimization approach for selection of energy storage systems, Comput. Chem. Eng. (2018). https://doi.org/10.1016/j.compchemeng.2018.04.014.

[18] S.B. Walker, U. Mukherjee, M. Fowler, A. Elkamel, Benchmarking and selection of Power-to-Gas utilizing electrolytic hydrogen as an energy storage alternative, Int. J. Hydrogen Energy. (2016). https://doi.org/10.1016/j.ijhydene.2015.09.008.

[19] B. Özkan, İ. Kaya, U. Cebeci, H. Başlıgil, A Hybrid Multicriteria Decision Making Methodology Based on Type-2 Fuzzy Sets For Selection Among Energy Storage Alternatives, Int. J. Comput. Intell. Syst. (2015). https://doi.org/10.1080/18756891.2015.1084715.

[20] I. Dincer, Evaluation and selection of energy storage systems for solar thermal

applications, Int. J. Energy Res. (1999). https://doi.org/10.1002/(SICI)1099-114X(19991010)23:12<1017::AID-ER535>3.0.CO;2-Q.

[21] X. Liu, P. Guo, S. Guo, Assessing the eco-efficiency of a circular economy system in China's coal mining areas: Emergy and data envelopment analysis, J. Clean. Prod. 206 (2019) 1101–1109. https://doi.org/10.1016/j.jclepro.2018.09.218.

[22] W. Liu, J. Zhan, Z. Li, S. Jia, F. Zhang, Y. Li, Eco-efficiency evaluation of regional circular economy: A case study in Zengcheng, Guangzhou, Sustain. (2018). https://doi.org/10.3390/su10020453.

[23] M. Hindiyeh, T. Altalafha, M. Al-Naerat, H. Saidan, A. Al-Salaymeh, L. Sbeinati, M. Saidan, Process Modification of Pharmaceutical Tablet Manufacturing Operations: An Eco-Efficiency Approach, Processes. 6 (2018) 15. https://doi.org/10.3390/pr6020015.

[24] K. Richa, C.W. Babbitt, G. Gaustad, Eco-Efficiency Analysis of a Lithium-Ion Battery Waste Hierarchy Inspired by Circular Economy, J. Ind. Ecol. 21 (2017) 715–730. https://doi.org/10.1111/jiec.12607.

[25] X. Wang, H. Ding, L. Liu, Eco-efficiency measurement of industrial sectors in China: A hybrid super-efficiency DEA analysis, J. Clean. Prod. (2019). https://doi.org/10.1016/j.jclepro.2019.05.014.

[26] V. Moutinho, J.A. Fuinhas, A.C. Marques, R. Santiago, Assessing eco-efficiency through the DEA analysis and decoupling index in the Latin America countries, J. Clean. Prod. 205 (2018) 512–524.

https://doi.org/10.1016/j.jclepro.2018.08.322.

[27] R. Kiani Mavi, R.F. Saen, M. Goh, Joint analysis of eco-efficiency and eco-innovation with common weights in two-stage network DEA: A big data approach, Technol. Forecast. Soc. Change. (2018) 1–10. https://doi.org/10.1016/j.techfore.2018.01.035.

[28] A. Charnes, W.W. Cooper, E. Rhodes, Measuring the efficiency of decision making units, Eur. J. Oper. Res. (1978). https://doi.org/10.1016/0377-2217(78)90138-8.

[29] R.D. Banker, Estimating most productive scale size using data envelopment analysis, Eur. J. Oper. Res. (1984). https://doi.org/10.1016/0377-2217(84)90006-7.

[30] X. Chen, Z. Gong, DEA efficiency of energy consumption in China's manufacturing sectors with environmental regulation policy constraints, Sustain. (2017). https://doi.org/10.3390/su9020210.

[31] S.K. Lee, G. Mogi, S.C. Shin, J.W. Kim, An AHP/DEA hybrid model for measuring the relative efficiency of energy efficiency technologies, in: IEEM 2007 2007 IEEE Int. Conf. Ind. Eng. Eng. Manag., 2007. https://doi.org/10.1109/IEEM.2007.4419150.

[32] B. Yilmaz, M.A. Yurdusev, Use of data envelopment analysis as a multi criteria decision tool - A case of irrigation management, Math. Comput. Appl. 16 (2011) 669–679. https://doi.org/10.3390/mca16030669.

[33] Y. Fan, B. Bai, Q. Qiao, P. Kang, Y. Zhang, J. Guo, Study on eco-efficiency of

industrial parks in China based on data envelopment analysis, J. Environ. Manage. 192 (2017) 107–115. https://doi.org/10.1016/j.jenvman.2017.01.048.

[34] W.W. Cooper, L.M. Seiford, K. Tone, Introduction to data envelopment analysis and its uses: With DEA-solver software and references, 2006. https://doi.org/10.1007/0-387-29122-9.

[35] A. Emrouznejad, G.R. Amin, DEA models for ratio data: Convexity consideration, Appl. Math. Model. 33 (2009). https://doi.org/10.1016/j.apm.2007.11.018.

[36] U. Shetty, T.P.M. Pakkala, Ranking efficient DMUs based on single virtual inefficient DMU in DEA, OPSEARCH. 47 (2010). https://doi.org/10.1007/s12597-010-0004-3.

[37] S. Ziari, S. Raissi, Ranking efficient DMUs using minimizing distance in DEA, J. Ind. Eng. Int. 12 (2016). https://doi.org/10.1007/s40092-016-0141-2.

[38] R. Lin, Y. Liu, Y. Man, J. Ren, Towards a sustainable distributed energy system in China: Decision-making for strategies and policy implications, Energy. Sustain. Soc. (2019). https://doi.org/10.1186/s13705-019-0237-9.

[39] B. Purvis, Y. Mao, D. Robinson, Three pillars of sustainability: in search of conceptual origins, Sustain. Sci. (2019). https://doi.org/10.1007/s11625-018-0627-5.

[40] F. Asche, T.M. Garlock, J.L. Anderson, S.R. Bush, M.D. Smith, C.M. Anderson, J. Chu, K.A. Garrett, A. Lem, K. Lorenzen, A. Oglend, S. Tveteras, S. Vannuccini, Three pillars of sustainability in fisheries, Proc. Natl. Acad. Sci. U. S. A. (2018).

https://doi.org/10.1073/pnas.1807677115.

[41] R. Lin, Y. Man, C.K.M. Lee, P. Ji, J. Ren, Sustainability prioritization framework of biorefinery: A novel multi-criteria decision-making model under uncertainty based on an improved interval goal programming method, J. Clean. Prod. (2020). https://doi.org/10.1016/j.jclepro.2019.119729.

[42] A. Lagrange, M. de Simón-Martín, A. González-Martínez, S. Bracco, E. Rosales-Asensio, Sustainable microgrids with energy storage as a means to increase power resilience in critical facilities: An application to a hospital, Int. J. Electr. Power Energy Syst. (2020). https://doi.org/10.1016/j.ijepes.2020.105865.

[43] S. Sabihuddin, A.E. Kiprakis, M. Mueller, A numerical and graphical review of energy storage technologies, Energies. 8 (2015) 172–216. https://doi.org/10.3390/en8010172.

[44] F. Díaz-González, A. Sumper, O. Gomis-Bellmunt, R. Villafáfila-Robles, A review of energy storage technologies for wind power applications, Renew. Sustain. Energy Rev. 16 (2012) 2154–2171. https://doi.org/10.1016/j.rser.2012.01.029.

[45] D. Murrant, J. Radcliffe, Assessing energy storage technology options using a multi-criteria decision analysis-based framework, Appl. Energy. 231 (2018) 788–802. https://doi.org/10.1016/j.apenergy.2018.09.170.

[46] C. Friebe, A. Lex-Balducci, U.S. Schubert, Sustainable Energy Storage: Recent Trends and Developments toward Fully Organic Batteries, ChemSusChem. 12 (2019) 4093–4115. https://doi.org/10.1002/cssc.201901545.

[47] B. Llamas, M.F. Ortega, G. Barthelemy, I. de Godos, F.G. Acién, Development of an efficient and sustainable energy storage system by hybridization of compressed air and biogas technologies (BIO-CAES), Energy Convers. Manag. (2020). https://doi.org/10.1016/j.enconman.2020.112695.

[48] J. Ren, Sustainability prioritization of energy storage technologies for promoting the development of renewable energy: A novel intuitionistic fuzzy combinative distance-based assessment approach, Renew. Energy. 121 (2018) 666–676. https://doi.org/10.1016/j.renene.2018.01.087.

[49] D.P. Hanak, V. Manovic, Linking renewables and fossil fuels with carbon capture via energy storage for a sustainable energy future, Front. Chem. Sci. Eng. 14 (2020) 453–459. https://doi.org/10.1007/s11705-019-1892-2.

[50] M. Baumann, M. Weil, J.F. Peters, N. Chibeles-Martins, A.B. Moniz, A review of multi-criteria decision making approaches for evaluating energy storage systems for grid applications, Renew. Sustain. Energy Rev. 107 (2019) 516–534. https://doi.org/10.1016/j.rser.2019.02.016.

[51] H. Ait Ousaleh, S. Sair, A. Zaki, A. Faik, J. Mirena Igartua, A. El Bouari, Double hydrates salt as sustainable thermochemical energy storage materials: Evaluation of dehydration behavior and structural phase transition reversibility, Sol. Energy. 201 (2020) 846–856. https://doi.org/10.1016/j.solener.2020.03.067.

[52] G. Fuchs, B. Lunz, M. Leuthold, D.U. Sauer, Technology Overview on Electricity Storage - Overview on the potential and on the deployment perpectives of electric storage technologies, Inst. Power Electron. Electr. Drives

(ISEA), RWTH Aachen Univ. (2012) 66. https://doi.org/10.13140/RG.2.1.5191.5925.

[53] M.C. Díaz-Ramírez, V.J. Ferreira, T. García-Armingol, A.M. López-Sabirón, G. Ferreira, Environmental assessment of electrochemical energy storage device manufacturing to identify drivers for attaining goals of sustainable materials 4.0, Sustain. 12 (2020). https://doi.org/10.3390/su12010342.

[54] Y.S.H. Najjar, A.M. Abubaker, Using novel compressed-air energy storage systems as a green strategy in sustainable power generation–a review, Int. J. Energy Res. 40 (2016) 1595–1610. https://doi.org/10.1002/er.3550.

[55] A. Evans, V. Strezov, T.J. Evans, Assessment of utility energy storage options for increased renewable energy penetration, Renew. Sustain. Energy Rev. 16 (2012) 4141–4147. https://doi.org/10.1016/j.rser.2012.03.048.

[56] A. Chatzivasileiadi, E. Ampatzi, I. Knight, Characteristics of electrical energy storage technologies and their applications in buildings, Renew. Sustain. Energy Rev. 25 (2013) 814–830. https://doi.org/10.1016/j.rser.2013.05.023.

[57] H.L. Ferreira, R. Garde, G. Fulli, W. Kling, J.P. Lopes, Characterisation of electrical energy storage technologies, Energy. 53 (2013) 288–298. https://doi.org/10.1016/j.energy.2013.02.037.

[58] A.K. Rohit, K.P. Devi, S. Rangnekar, An overview of energy storage and its importance in Indian renewable energy sector: Part I – Technologies and Comparison, J. Energy Storage. 13 (2017) 10–23. https://doi.org/10.1016/j.est.2017.06.005.

[59] V. Jülch, Comparison of electricity storage options using levelized cost of storage (LCOS) method, Appl. Energy. 183 (2016) 1594–1606. https://doi.org/10.1016/j.apenergy.2016.08.165.

[60] L. Stamford, A. Azapagic, Life cycle sustainability assessment of UK electricity scenarios to 2070, Energy Sustain. Dev. 23 (2014) 194–211. https://doi.org/10.1016/j.esd.2014.09.008.

[61] X. Tan, Q. Li, H. Wang, Advances and trends of energy storage technology in Microgrid, Int. J. Electr. Power Energy Syst. 44 (2013) 179–191. https://doi.org/10.1016/j.ijepes.2012.07.015.

[62] A.T. Gumus, A. Yesim Yayla, E. Çelik, A. Yildiz, A combined fuzzy-AHP and fuzzy-GRA methodology for hydrogen energy storage method selection in Turkey, Energies. 6 (2013) 3017–3032. https://doi.org/10.3390/en6063017.

[63] X. Xu, R. Chen, F. He, L. Zhu, Two non-radial measures of super-efficiency in DEA with data uncertainty, J. Intell. Fuzzy Syst. 32 (2017) 4533–4542. https://doi.org/10.3233/JIFS-169217.

[64] A. Sengupta, T.K. Pal, On comparing interval numbers, Eur. J. Oper. Res. (2000). https://doi.org/10.1016/S0377-2217(99)00319-7.

[65] M. Melikoglu, Pumped hydroelectric energy storage: Analysing global development and assessing potential applications in Turkey based on Vision 2023 hydroelectricity wind and solar energy targets, Renew. Sustain. Energy Rev. 72 (2017). https://doi.org/10.1016/j.rser.2017.01.060.

[66] I. Kougias, S. Szabó, Pumped hydroelectric storage utilization assessment:

Forerunner of renewable energy integration or Trojan horse?, Energy. 140 (2017). https://doi.org/10.1016/j.energy.2017.08.106.

[67] C.J. Yang, Pumped Hydroelectric Storage, in: Storing Energy With Spec. Ref. to Renew. Energy Sources, 2016. https://doi.org/10.1016/B978-0-12-803440-8.00002-6.

[68] D. Connolly, S. MacLaughlin, M. Leahy, Development of a computer program to locate potential sites for pumped hydroelectric energy storage, Energy. 35 (2010). https://doi.org/10.1016/j.energy.2009.10.004.

[69] N. Hartmann, O. Vöhringer, C. Kruck, L. Eltrop, Simulation and analysis of different adiabatic Compressed Air Energy Storage plant configurations, Appl. Energy. 93 (2012). https://doi.org/10.1016/j.apenergy.2011.12.007.

[70] M. Budt, D. Wolf, R. Span, J. Yan, A review on compressed air energy storage: Basic principles, past milestones and recent developments, Appl. Energy. 170 (2016). https://doi.org/10.1016/j.apenergy.2016.02.108.

[71] Y. Li, S. Miao, X. Luo, B. Yin, J. Han, J. Wang, Dynamic modelling and techno-economic analysis of adiabatic compressed air energy storage for emergency back-up power in supporting microgrid, Appl. Energy. 261 (2020). https://doi.org/10.1016/j.apenergy.2019.114448.

[72] E. Hammann, R. Madlener, C. Hilgers, Economic Feasibility of a Compressed Air Energy Storage System under Market Uncertainty: A Real Options Approach, in: Energy Procedia, 2017. https://doi.org/10.1016/j.egypro.2017.03.888.

[73] J. Büngeler, E. Cattaneo, B. Riegel, D.U. Sauer, Advantages in energy efficiency

of flooded lead-acid batteries when using partial state of charge operation, J. Power Sources. 375 (2018). https://doi.org/10.1016/j.jpowsour.2017.11.050.

[74] H. Jafari, M.R. Rahimpour, Pb Acid Batteries, in: Recharg. Batter., 2020. https://doi.org/10.1002/9781119714774.ch2.

[75] S. Anuphappharadorn, S. Sukchai, C. Sirisamphanwong, N. Ketjoy, Comparison the economic analysis of the battery between lithium-ion and lead-acid in PV stand-alone application, in: Energy Procedia, 2014. https://doi.org/10.1016/j.egypro.2014.07.167.

[76] A. Jaiswal, Lithium-ion battery based renewable energy solution for off-grid electricity: A techno-economic analysis, Renew. Sustain. Energy Rev. 72 (2017). https://doi.org/10.1016/j.rser.2017.01.049.

[77] S. Saeidnia, M. Abdollahi, Concerns on the growing use of lithium: The pros and cons, Iran. Red Crescent Med. J. 15 (2013). https://doi.org/10.5812/ircmj.13756.

[78] S. Sabihuddin, A.E. Kiprakis, M. Mueller, A numerical and graphical review of energy storage technologies, Energies. (2015). https://doi.org/10.3390/en8010172.

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

[80] L. Stougie, G. Del Santo, G. Innocenti, E. Goosen, D. Vermaas, H. van der Kooi, L. Lombardi, Multi-dimensional life cycle assessment of decentralised energy

storage systems, Energy. 182 (2019) 535–543. https://doi.org/10.1016/j.energy.2019.05.110.

[81] M. Matsumoto, Mersenne Twister: A 623-Dimensionally Equidistributed Uniform Pseudo-Random Number Generator Dedicated to the Memory of Nobuo Yoneda, ACM Trans. Model. Comput. Simul. 8 (1998).

[82] G.R. Jahanshahloo, F.H. Lotfi, M. Izadikhah, An algorithmic method to extend TOPSIS for decision-making problems with interval data, Appl. Math. Comput. (2006). https://doi.org/10.1016/j.amc.2005.08.048.

[83] M.K. Sayadi, M. Heydari, K. Shahanaghi, Extension of VIKOR method for decision making problem with interval numbers, Appl. Math. Model. 33 (2009). https://doi.org/10.1016/j.apm.2008.06.002.

[84] R.W. Saaty, The analytic hierarchy process-what it is and how it is used, Math. Model. (1987). https://doi.org/10.1016/0270-0255(87)90473-8.