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Sustainability Ranking of Energy Storage Technologies under Uncertainties

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Abstract: The selection of the most suitable or the best energy storage technology among multiple alternatives is of vital importance for promoting the development of renewable energy. This study aims at developing a multi-attribute decision analysis framework for sustainability prioritization of energy storage technologies. A criteria system which consists of ten criteria in four categories (economic, performance, technological and environmental) was developed for sustainability assessment of energy storage technologies. The Non-Linear Fuzzy Prioritization which allows the users to use fuzzy numbers to establish the comparison judgments was employed to determine the weights of the evaluation criteria, and a novel interval multi-attribute decision analysis method which can rank the alternative energy storage technologies based on the interval decision-making matrix was developed for sustainability prioritization of energy storage technologies. An illustrative case including five energy storage technologies including pumped hydro (PH), compressed air (CA), Lead-Acid (LA), Lithium-ion (LI), and Flywheel (FW) was studied by the proposed method, and PH was recognized as the most sustainable technology. The results were validated by the interval TOPSIS method, and sensitivity analysis was also carried out to investigate the effects of the weights of the evaluation criteria on the sustainability order of the five energy storage technologies.

Keywords: energy storage technology; multi-attribute decision analysis; fuzzy set: interval numbers

1. Introduction

The global electricity generation increased dramatically over the past years, around 70% of the electricity was produced from fossil fuels (coal, natural gas and oil), and the promotion of electricity based on renewable energy sources is critical for global warming potential mitigation and maintaining the power network stability (Luo *et al*., 2015). However, the development of renewable energy based electricity faces various barriers and challenges, i.e. high capital cost, high production cost, low maturity, and intermittency (Luthra *et al*., 2015; Ahlborg and Hammar, 2014). Among these, intermittency is one of the most critical barriers. The development of energy storage technologies is of vital importance for promoting the development of renewable energy. There are various energy storage technologies (i.e. capacitors, flywheel, lead-acid batteries, lithium-ion batteries, compressed-air energy storage, pumped-hydro storage, and thermal energy storage, etc.), and different energy storage technologies have different properties and performances, i.e. power rating, discharge time, energy and power density, life time, and cycling capacity, etc. (Akinyele and Rayudu, 2014). Similarly, the costs and technological maturity levels of different energy storage technologies are also different. Accordingly, it is usually difficult for the decision-makers to select the most suitable or the best scenario among multiple energy storage technologies when facing various conflicting criteria. Meanwhile, it is apparent that the selection or the evaluation of energy storage technologies is a multi-attribute decision analysis (MADA) or so-called "multi-criteria decision making" (MCDM) problem.

There are various MADA or MCDM methods which have been developed for the selection and prioritization of energy storage technologies. Barin *et al.* (2009) developed a multi-criteria decision making (MCDM) model by integrating Analytic Hierarchy Process (AHP) and fuzzy logic to evaluate the operations of five energy storage systems, including pumped hydro storage, compressed air energy storage, H_2 storage, flywheel and super-capacitors, and the relative priorities of these five energy storage technologies were determined by AHP based on human judgments. Fuzzy Delphi method, AHP, and fuzzy consistent matrix were combined to evaluate three energy storage technologies, namely, pumped hydro storage, compressed air energy storage, and sodium sulfur battery storage, and the priority values of these three energy storage technologies with respect to each evaluation criterion were obtained based on the judgments of the experts (Daim *et al.*, 2012). Gim and Kim (2014) used fuzzy AHP to evaluate five hydrogen storage systems (350 bar compressed gas hydrogen, 700 bar compressed gas hydrogen, liquefied hydrogen, metal hydride, and chemical hydride) for automobiles in Korea, and the data were obtained from two ways: some were obtained from literature, and some were scored by the experts by classifying these five hydrogen storage systems into five groups (best, good, middle, bad and worst) according to their relative performances with respect to each evaluation criterion. Gumus *et al.* (2013) developed a MCDM method by combining the Buckley extension based fuzzy AHP and the linear normalization based fuzzy Grey Relational Analysis (GRA) for the selection of hydrogen storage methods in Turkey, three hydrogen storage technologies including tank, metal hydride and chemical were studied, and the data of these three alternative hydrogen storage technologies were scored by the decision-makers. Montignac *et al*. (2015) employed the MACBETH method as the MCDM method to evaluate hydrogen storage systems for future vehicles. Özkan *et al*. (2015) developed a hybrid MCDM technique by combing AHP and type-2 fuzzy TOPSIS method, the results reveal that the proposed technique can help the users to select the most suitable electrical energy storage alternative among multiple scenario based on their experience and judgments. All these studies are beneficial for the users to select the most suitable or the best energy storage technology among multiple alternatives; however, there is also a critical research gap- most of the previous research ranked the energy storage merely based on human judgments, thus, some useful data cannot be fully used in the decision-making process. This study aims at developing a multi-criteria decision supporting framework for sustainability prioritization of energy storage technologies which can incorporate both hard and soft criteria, a fuzzy set based weighting method which can incorporate the preference/opinions of the decision-makers was employed to determine the weights of the evaluation criteria, and an interval multi-attribute decision analysis method was developed to rank the energy storage technologies according to their sustainability. Compared with the previous published works, the developed sustainability ranking framework for prioritizing the alternative energy storage technologies has the following innovations:

(1) Completion of criteria system: both the hard and the soft criteria in multiple dimensions (i.e. economic, performance, technological, and environmental) for sustainability assessment of energy storage technologies were considered for ranking the alternative energy storage technologies;

(2) Accurate weights determination: the non-linear fuzzy prioritization method which employs the fuzzy triangular numbers to represent the opinions/preferences of a criterion over another can capture the vagueness and ambiguity existing in human's judgments;

(3) Decision-making under uncertainties: a novel interval multi-attribute decision analysis which can address uncertainties to rank the alternative energy storage technologies based on the decision-making matrix which was composed by the interval numbers was developed, and the interval numbers were used to describe the possible variation ranges of the alternative energy storage technologies with respect to the criteria for sustainability assessment.

Besides the introduction, the remaindering parts of this study has been organized as follows: section 2 presented the criteria system for sustainability assessment of energy storage technologies; section 3 proposed the weighting method based on fuzzy set theory and developed the interval multi-attribute decision analysis method for prioritizing the energy storage technologies; an illustrative case which includes five energy storage technologies has been studied by developed framework in section 4; sensitivity analysis has been carried out to investigate the effects of the weights on the sustainability ranking of these five energy storage technologies, and the proposed interval multi-attribute decision analysis method has been validated by the interval TOPSIS method in section 5; and this study has been concluded in section 6.

2. Criteria for sustainability assessment of energy storage technologies

There are various studies which have developed the criteria system for the selection and evaluation of energy storage technologies. For instance, six criteria including efficiency, load management, technical maturity, costs, lifecycle, and power quality were employed to evaluate energy storage systems (Barin *et al.,* 2009). Daim *et al.* (2012) developed a criteria system for the evaluation of energy storage technologies which consists four perspectives, including technical perspective (efficiency, maturity, capacity, lifetime, response delay time, durability, power density, self-discharge, energy density, power transmission rate, autonomy), economic perspective (capital costs, operations and maintenance costs, end of life costs, fuel costs, emission costs, and recurrent costs), environmental perspective (air pollution, water pollution, land disruption, and wildlife impacts), and social perspective (security, health and safety, social acceptance, and job creation). Gim and Kim (2014) used eight criteria in five dimensions including storage efficiency (weight efficiency and volume efficiency), economy (system cost and energy efficiency), durability

&operability (refueling time and cycle time), safety, and infrastructure to evaluate the priorities of hydrogen storage systems. Gumus *et al.* (2013) employed weightlessness, capacity, storage loss and leak, reliability, and total system cost to evaluate hydrogen storage technologies. Similarly, five criteria including volume, mass, conformability, H_2 loss rate, and refueling time were used for the evaluation of hydrogen storage systems for future vehicles.

The criteria system is of vital importance for sustainability prioritization of energy storage technologies, and a complete criteria system can accurately evaluate the integrated priorities of the energy storage technologies. However, there is not a unique standard for establishing the criteria systems for the evaluation of energy storage technologies, because different users have different preferences. This study aims at evaluating the sustainability of energy storage technologies, and the criteria system was established based on a focus group meeting after literature reviews. A criteria system which consists of ten criteria in four categories, including economic (i.e. capital cost, life, and operating cost), performance (i.e. energy efficiency, materials intensity, energy intensity, and energy density), technological (maturity), and environmental (CO_2 intensity and environmental impact), was developed for sustainability assessment of energy storage technologies in this study. It is worth pointing out that the users can add more or/and delete some criteria from the developed criteria system for the evaluation of the energy storage technologies according to their preferences and the actual conditions.

3. Methods

The weighting method was firstly introduced in this part: then, the multi-attribute decision analysis (MADA) under uncertainties was developed for ranking the alternatives.

3.1 Weighting method

There are various methods which can be used for weights determination. The most famous is the Analytic Hierarchy Process (AHP) and various modified AHP methods. In order to overcome the weak points of the traditional AHP on capturing uncertainties, subjectivity and ambiguity, there are various modified AHP methods by incorporating the thoughts of AHP and fuzzy set theory. For instance, Chang (1996) developed the fuzzy AHP which allows the users to employ the triangular fuzzy numbers to establish the comparison matrix. Wang et al. (2006) developed the modified fuzzy logarithmic least squares method for fuzzy analytic hierarchy process to determine the weights of the criteria. All these fuzzy AHP methods can successfully address the ambiguity and uncertainties existing in human's opinions, but there are still some problems which influence the convenience of the use of these methods: (i)The users need to construct the complete pair-wise comparison matrix, and they do not allow the users to determine the weights/priorities with an incomplete set of judgments; (ii) the complexity and difficulty in computations. Mikhailov (2003) developed a novel weight determination method, so-called "Non-Linear Fuzzy Prioritization (NLFP)" method, for determining the weights/priorities by using a max-min optimization approach. The NLFP can overcome the above-mentioned two weaknesses of the other fuzzy AHP methods. The NLFP method which is a method based on fuzzy set theory was employed for weights determination in this study. Accordingly, fuzzy set theory was introduced in section 3.1.1, and the NLFP method was specified in section 3.1.2.

3.1 .1 Fuzzy set

The real world usually faces many problems with several of uncertainties, imprecise information, and ambiguities. Zadeh (1965) developed the fuzzy set instead of the crisp numbers to describe the uncertainties by incorporating the concept of membership.

Definition 1. Fuzzy sets (Zadeh, 1965)

As for an universal discourse A comprised by the elements a, the fuzz set α in A can be defined as a set of ordered pairs. $\mu_\alpha(x)$ represents the level of certainty that α belongs to the fuzzy set α.

$$\alpha = \left\{(a, \mu_\alpha(a)) \mid a \in A\right\} \tag{1}$$

where $\mu_\alpha(a)$ is the membership function of a in α.

Definition 2. Triangular fuzzy numbers (TFM) (Chang, 1996)

The TFM $\tilde{A}$ is a triple-tuple $\tilde{A} = \left(a^1, a^2, a^3\right)$. The membership of x with respect to fuzzy set $\tilde{A}$ was presented in Eq.2, it can also be graphically represented by Figure 1.

$$\mu_{\tilde{A}}(x) = \begin{cases} 0 & x \le a^1 \\ \dfrac{x - a^1}{a^2 - a^1} & a^1 < x \le a^2 \\ \dfrac{a^3 - x}{a^3 - a^2} & a^2 < x \le a^3 \\ 0 & x > a^3 \end{cases} \tag{2}$$

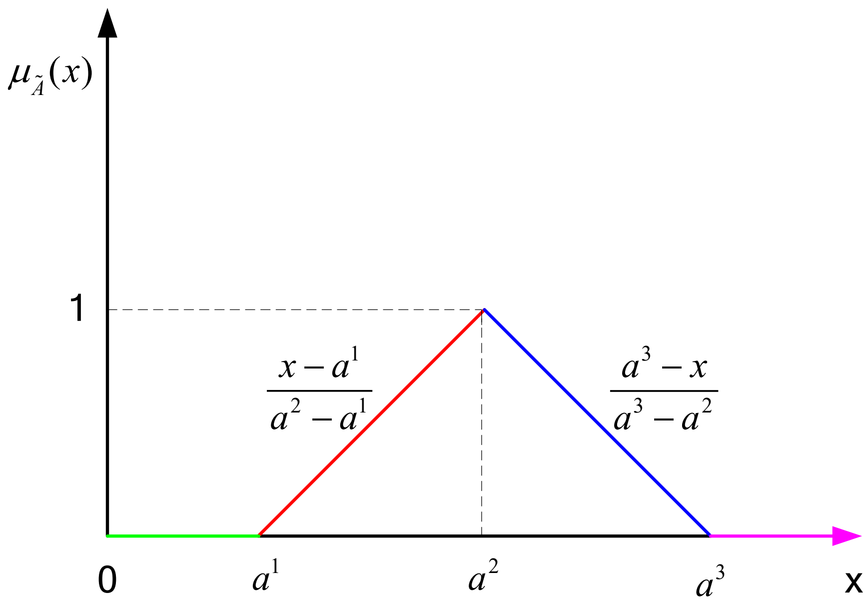

Figure 1: Triangular fuzzy set $\tilde{A}=\left(a^1,a^2,a^3\right)$

Definition 3. Arithmetic operations (Chang ,1996; Yuen and Lau ,2011; Chen, 2000)

The arithmetic operations between the triangular fuzzy numbers were presented in Table 1.

Table 1: The arithmetic operations between the triangular fuzzy numbers

	$\tilde{A}=\left(a^1,a^2,a^3\right)$ and $\tilde{B}=\left(b^1,b^2,b^3\right)$ are two triangular fuzzy numbers, and $\lambda>0,\lambda\in R$	
Addition	$\tilde{A}+\tilde{B}=\left(a^1,a^2,a^3\right)+\left(b^1,b^2,b^3\right)=\left(a^1+b^1,a^2+b^2,a^3+b^3\right)$	(3)
Subtraction	$\tilde{A}-\tilde{B}=\left(a^1,a^2,a^3\right)-\left(b^1,b^2,b^3\right)=\left(a^1-b^3,a^2-b^2,a^3-b^1\right)$	(4)
Multiplication	$\tilde{A}\otimes\tilde{B}=\left(a^1,a^2,a^3\right)\otimes\left(b^1,b^2,b^3\right)=\left(a^1b^1,a^2b^2,a^3b^3\right)$	(5)
Scalar	$\lambda\tilde{A}=\lambda\left(a^1,a^2,a^3\right)=\left(\lambda a^1,\lambda a^2,\lambda a^3\right)$	(6)
Division	$\tilde{A}\div\tilde{B}=\left(a^1,a^2,a^3\right)\div\left(b^1,b^2,b^3\right)=\left(a^1/b^2,a^2/b^2,a^3/b^1\right)$	(7)
Reciprocal	$\frac{1}{\tilde{A}}=\frac{1}{\left(a^1,a^2,a^3\right)}=\left(\frac{1}{a^3},\frac{1}{a^2},\frac{1}{a^1}\right)$	(8)
Euclidean distance	$d\left(\tilde{A},\tilde{B}\right)=\left[\left(a^1-b^1\right)^2+\left(a^2-b^2\right)^2+\left(a^3-b^3\right)^2\right]^{1/2}$	(9)
	where $0<a^1\le a^2\le a^3$ and $0<b^1\le b^2\le b^3$	

3.1.2 Non-Linear Fuzzy Prioritization

The NLFP method consists of three steps, and they are (i) determining the fuzzy pair-wise comparison judgments by using linguistic variables;(ii) determining the fuzzy pair-wise comparison judgments by using triangular fuzzy numbers; and (iii) establishing the non-linear optimization programming for obtaining the weights of the criteria. These three steps have been specified as follows (Mikhailov, 2003):

Step 1: determining the fuzzy pair-wise comparison judgments. Assuming that there are a total of n elements ($e_i(i=1,2,\cdots,n)$) to be studied, and the users are firstly asked to use the linguistic variables including 'equally important', 'weakly important', 'moderately important', 'moderately plus', 'strongly important', 'strongly plus', 'very strongly', 'very, very strongly', 'extremely important', and their reciprocals to determine the relative preference rating of an element over another (Yuen and Lau, 2011). Note that the users only need to compare each pair of elements once. For instance, if the users compared the relative preference of the *i*-th element over the *j*-th element, they do not need to compare the relative preference of the *j*-th element over the *i*-th element.

Step 2: determining the fuzzy pair-wise comparison judgments by using triangular fuzzy numbers. All the elements in the comparison judgments determined in Step 1 can be transformed into triangular fuzzy numbers according to Figure 2. Note that the linguistic ′equal importance ′ (EI) which corresponds to (1,1,1) will be used to depict the relative preference if the two elements have been recognized equal importance.

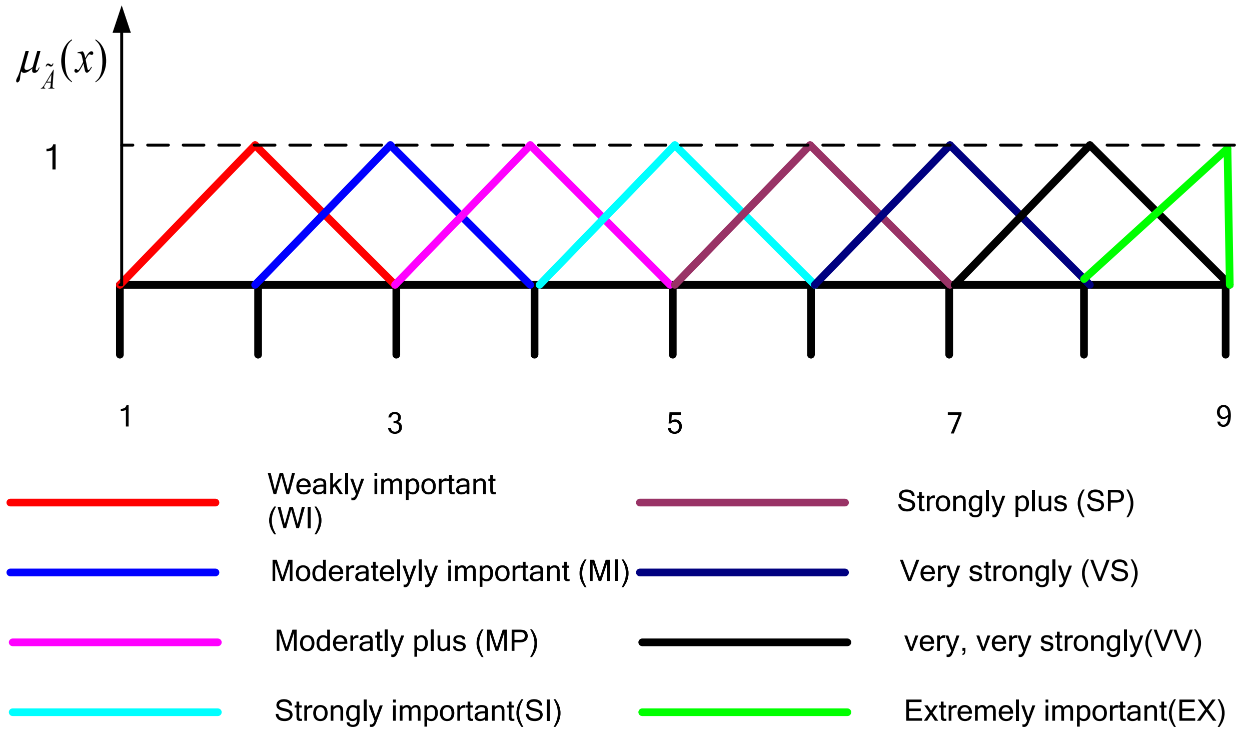

Figure 2: The linguistic variables and their corresponding triangulzr fuzzy numbers

After the transformation, the pair-wise comparison matrix for these n elements can be accordingly determined, as presented in Eq.10.

$$\begin{array}{cccccc} & e_1 & e_2 & e_3 & \cdots & e_n \\ e_1 & / & A_{12} & A_{13} & \cdots & A_{1n} \\ e_2 & & / & A_{23} & \cdots & A_{2n} \\ \vdots & & & / & \vdots & \vdots \\ e_{n-1} & & & & \ddots & A_{(n-1)n} \\ e_n & & & & & / \end{array} \tag{10}$$

where $A_{ij} = (a_{ij}^1, a_{ij}^2, a_{ij}^3)$ is a triangular number which represents the relative preference of the *i*-th element over the *j*-th element.

Step 3: establishing the non-linear optimization programming for obtaining the weights of the criteria.

The crisp weight vector should satisfy or appropriately satisfy the initial fuzzy judgments $A_{ij}=(a_{ij}^1,a_{ij}^2,a_{ij}^3) \quad i=1,2,\cdots,n-1; j=1,2,\cdots,n, j>i$. Accordingly, it could be obtained that

$$a_{ij}^1 \le \omega_i / \omega_j \le a_{ij}^3 \tag{11}$$

A membership function which is linear to the ratio ω_i / ω_j, can be established for each fuzzy judgment.

$$\mu_{ij}\left(\omega_i / \omega_j\right)=\begin{cases}\left(\omega_i / \omega_j - a_{ij}^1\right)/(a_{ij}^2-a_{ij}^1) & \omega_i / \omega_j \le a_{ij}^2 \\ \left(a_{ij}^3-\omega_i / \omega_j\right)/(a_{ij}^3-a_{ij}^2) & \omega_i / \omega_j \ge a_{ij}^2\end{cases} \tag{12}$$

Eq. 5 linearly increases and decreases on the intervals $\left(-\infty, a_{ij}^2\right)$ and $\left(a_{ij}^2,\infty\right)$, respectively. The value of $\mu_{ij}\left(\omega_i / \omega_j\right)$ is less than zero when $\omega_i / \omega_j < a_{ij}^1$ or $\omega_i / \omega_j > a_{ij}^3$, and it takes the maximum value 1 when $\omega_i / \omega_j = a_{ij}^2$. Therefore, the membership function coincides with the fuzzy judgment $A_{ij}=(a_{ij}^1,a_{ij}^2,a_{ij}^3) \quad i=1,2,\cdots,n-1; j=1,2,\cdots,n, j>i$ over the interval $\left(a_{ij}^2, a_{ij}^3\right)$.

Let $\lambda=\mu_{ij}\left(\omega_i / \omega_j\right)$, the optimal weights can be obtained by finding the maximizing solution by using a max-min approach:

$$\begin{aligned}&\max \quad \lambda \\ &\left(a_{ij}^2-a_{ij}^1\right)\lambda\omega_j-\omega_i+a_{ij}^1\omega_j \le 0 \qquad i=1,2,\cdots,n-1; j=1,2,\cdots,n, j>i \\ &\left(a_{ij}^3-a_{ij}^2\right)\lambda\omega_j+\omega_i-a_{ij}^3\omega_j \le 0 \qquad i=1,2,\cdots,n-1; j=1,2,\cdots,n, j>i \\ &\sum_{i=1}^{n}\omega_i=1 \\ &\omega_i>0, i=1,2,\cdots,n\end{aligned} \tag{13}$$

where λ represents the consistency index, $\omega_i\left(i=1,2,\cdots,n\right)$ represents the weight of the *i*-th element

This is a non-linear optimization programming for calculating the weights of the n elements. After solving programming (4), the optimum value of λ, denoting by λ^* and $\omega_i^*\left(i=1,2,\cdots,n\right)$ can be accordingly determined. The optimum value of λ is a measure of the overall consistency, and if $\lambda > 0$, it indicates that all solution ratios completely satisfy the initial judgments, i.e. $a_{ij}^1 \leq \omega_i / \omega_j \leq a_{ij}^3$. However, if $\lambda < 0$, it indicates that the fuzzy judgments are very inconsistent and the solution ratios can only appropriately satisfy the initial judgments.

3.2 Interval multi-attribute decision analysis

It is usually difficult for the users to obtain the exact data of the alternatives with respect to the criteria for sustainability due to various uncertainties which refer to the imprecise measurement of an object due to various reasons, i.e. the lack of knowledge and system variations. Accordingly, sometime it is difficult or even impossible for the users to use exact data to describe the performance of an alternative with research to the criteria for sustainability assessment. Interval numbers which can depict the range of data variations can successfully resolve the uncertainties problems. Therefore, the traditional multi-attribute decision analysis method has been extened to uncertainty conditions, and an interval multi-attribute decision analysis (MADA) method has been developed to rank the alternative energy storage technologies under uncertainties.

3.2.1 Interval approach for uncertainties

Definition 4. Nonnegative interval number (Xu and Da, 2002)

A nonnegative interval number (NIN) can be defined as:

$$a=\left[a_L,a_U\right]=\left\{x\middle|0\leq a_L\leq x\leq a_U\right\} \tag{14}$$

a will turn into a crisp number when $a_L = a_U$.

It represents that its value range is between a_L and a_U. A NIN can alternatively be represented by its mid-point and half-width, as presented in Eq.15 and Eq.16, respectively.

$$MP(a) = \frac{a_L + a_U}{2} \tag{15}$$

$$HW(a) = \frac{a_U - a_L}{2} \tag{16}$$

where $MP(a)$ represents the mid-point of a, and $HW(a)$ is the half width of a.

Definition 5. Arithmetic operations between NINs (Sengupta and Pal, 2000).

The arithmetic operations between NINs can be defined in Table 2.

Table 2: The arithmetic operations between NINs

	$a = [a_L, a_U]$ and $b = [b_L, b_U]$ are two NINs, and $\lambda > 0, \lambda \in R$	
Addition	$a + b = [a_L, a_U] + [b_L, b_U] = [a_L + b_L, a_U + b_U]$	(17)
Subtraction	$a - b = [a_L, a_U] - [b_L, b_U] = [a_L - b_U, a_U - b_L]$	(18)
Multiplication	$a \otimes b = [a_L, a_U] \otimes [b_L, b_U] = [a_L b_L, a_U b_U]$	(19)
Scalar	$\lambda a = \lambda [a_L, a_U] = [\lambda a_L, \lambda a_U]$	(20)
Division	$a \div b = [a_L, a_U] \div [b_L, b_U] = \left[\frac{a_L}{b_U}, \frac{a_U}{b_L}\right]$	(21)

Definition 6. The probability of $a = [a_L, a_U] \geq b = [b_L, b_U]$ (Xu, 2008).

The probability of $a = [a_L, a_U] \geq b = [b_L, b_U]$ can be determined by Eq.22.

$$P(a \geq b) = \max\left\{1 - \max\left(\frac{b_U - a_L}{a_U - a_L + b_U - b_L}, 0\right), 0\right\} \tag{22}$$

Similarly, the probability of $b = [b_L, b_U] \geq a = [a_L, a_U]$ can be defined in Eq.23.

$$P(b \geq a) = \max\left\{1 - \max\left(\frac{a_U - b_L}{a_U - a_L + b_U - b_L}, 0\right), 0\right\} \tag{23}$$

According to Eq.22 and Eq.23, it could also be obtained that (Yager, 1988; Xu, 2008):

(i) $0 \leq P\left(a = [a_L, a_U] \geq b = [b_L, b_U]\right) \leq 1$ and $0 \leq P\left(b = [b_L, b_U] \geq a = [a_L, a_U]\right) \leq 1$;

(ii) $P\left(a = [a_L, a_U] \geq b = [b_L, b_U]\right) + P\left(b = [b_L, b_U] \geq a = [a_L, a_U]\right) = 1$;

(iii) $P\left(a = [a_L, a_U] \geq b = [b_L, b_U]\right) = P\left(b = [b_L, b_U] \geq a = [a_L, a_U]\right) = 0.5$ if and only if $a_L = b_L$ and $a_U = b_U$;

(iv) $P\left(a = [a_L, a_U] \geq b = [b_L, b_U]\right) > 0.5 > P\left(b = [b_L, b_U] \geq a = [a_L, a_U]\right) \Leftrightarrow a = [a_L, a_U] > b = [b_L, b_U]$

3.2.2 Interval multi-attribute decision analysis

The developed interval multi-attribute decision analysis (IMADA) consists of five steps including establishing the decision-making matrix, determining the ranking matrix, calculating the weighted ranking matrix, and determining the priority order of the alternatives.

Step 1: establishing the decision-making matrix. In this step, the users firstly determine the alternatives to be evaluated and the criteria for evaluating these alternatives. Assuming that there are a total of m alternatives (A_1, A_2,…,A_m) to be evaluated by n criteria (C_1, C_2,…,C_n), the decision-making matrix can then be determined, as presented in Table 3. All the elements in the decision-making matrix are interval numbers, and the weights of the criteria which were determined by the NLFP method.

Table 3: Interval decision-making matrix

	C_1	C_2	$\cdots$	C_n
A_1	$\left[y_{11}^l, y_{11}^u\right]$	$\left[y_{12}^l, y_{12}^u\right]$	$\cdots$	$\left[y_{1n}^l, y_{1n}^u\right]$
A_2	$\left[y_{21}^l, y_{21}^u\right]$	$\left[y_{22}^l, y_{22}^u\right]$	$\cdots$	$\left[y_{2n}^l, y_{2n}^u\right]$
$\vdots$	$\vdots$	$\vdots$	$\ddots$	$\vdots$
A_m	$\left[y_{m1}^l, y_{m1}^u\right]$	$\left[y_{m2}^l, y_{m2}^u\right]$	$\cdots$	$\left[y_{mn}^l, y_{mn}^u\right]$
Weights	ω_1	ω_2	$\cdots$	ω_n

where $\left[y_{ij}^l, y_{ij}^u\right]$ $i = 1, 2, \cdots, m; j = 1, 2, \cdots, n$ which is an interval number represents the value of the *i*-th alternative with respect to the *j*-th criterion, and ω_j $j = 1, 2, \cdots, n$ represents the weight of the *j*-th criterion.

Step 2: determining the ranking matrix.

These m alternative can be ranked according to the data of these alternatives with respect to each evaluation criterion. Taking the ranking of the m alternative with respect to the *j*-th criterion as an example:

The m interval numbers $\left[y_{1j}^l, y_{1j}^u\right], \left[y_{2j}^l, y_{2j}^u\right], \ldots, \left[y_{mj}^l, y_{mj}^u\right]$ can be ranked according to Eq.22, the comparison of the *k*-th alternative with the *t*-th alternative with respect to the *j*-th criterion can be determined by Eq.24.

$$p_{kt}^j = P\left(\left[y_{kj}^l, y_{kj}^u\right] \geq \left[y_{tj}^l, y_{tj}^u\right]\right) = \max\left\{1 - \max\left(\frac{y_{tj}^u - y_{kj}^l}{y_{tj}^u - y_{tj}^l + y_{kj}^u - y_{kj}^l}, 0\right), 0\right\} \tag{24}$$

where $p_{kt}^j = P\left(\left[y_{kj}^l, y_{kj}^u\right] \geq \left[y_{tj}^l, y_{tj}^u\right]\right)$ represents the possibility of the *k*-th alternative be greater than the *t*-th alternative with respect to the *j*-th criterion

After n(n-1)/2 times of comparisons, the following possibility matrix can be obtained, as presented in Eq.25.

$$P_j = \begin{array}{ccccc} C_j & A_1 & A_2 & \cdots & A_m \\ A_1 & p_{11}^j & p_{12}^j & \cdots & p_{1m}^j \\ A_2 & p_{21}^j & p_{22}^j & \vdots & p_{2m} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ A_m & p_{m1}^j & p_{m2}^j & \cdots & p_{mm}^j \end{array} \tag{25}$$

where P_j represents the possibility matrix for comparing the m alternatives with respect to the j-th criterion, and $p_{ii}^j = 0.5(i = 1, 2, \cdots, m)$.

Then, the priority score (PS) of each alternative with respect to the *j*-th criterion can be determined by Eq.26.

$$PS_i^j = \sum_{k=1}^{m} p_{ik}^j \tag{26}$$

where PS_i^j represents the priority score of the *i*-th alternative with respect to the *j*-th criterion.

Then, these m alternative can be ranked according to the rule that the greater the priority score, the better the corresponding alternative will be if the j-th criterion is the benefit-type criterion. While the smaller the priority score, the better the corresponding alternative will be if the j-th criterion is the cost-type criterion.

After determining the priority order of the m alternatives, the ranking matrix can be determined by Eqs.27-28.

$$\zeta_{it}^j = \begin{cases} 1, \text{if the i-th alternative has been ranked at the t-th position} \\ 0, \text{if the i-th alternative has not been ranked at the t-th position} \end{cases} \tag{27}$$

$$\zeta^j = \left\{ \zeta_{it}^j \right\}_{m \times m} \tag{28}$$

where ζ^j is the ranking matrix with respect to the j-th criterion, and ζ_{it}^j is the element in the ranking matrix with respect to the j-h criterion.

Step 3: Calculating the weighted ranking matrix (Li, 2003).

The weighted ranking matrix can be determined by Eqs.29-30.

$$\begin{array}{cccccc} & 1 & 2 & \cdots & m \\ A_1 & s_{11} & s_{12} & \cdots & s_{1m} \\ A_2 & s_{21} & s_{22} & \cdots & s_{2m} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ A_m & s_{m1} & s_{m2} & \cdots & s_{mm} \end{array} \tag{29}$$

$$s_{it} = \sum_{j=1}^{n} \varphi_{it}^{j} \omega_j \tag{30}$$

s_{it} can be recognized as the appropriateness of ranking the *i*-th alternative in the *t*-th position.

where s_{it} represents the element of cell (i, j) in the weighted ranking matrix.

Step 4: Determining the priority order of the alternatives (Li, 2003).

A linear 0-1 programming with the objective of maximizing the integrated appropriateness of the overall ranking of the alternatives was established to determine the priority order of the alternatives. The integrated appropriateness of the overall ranking of the alternatives can be represented by Eq.21.

$$Max\, S = \sum_{j=1}^{m} \sum_{t=1}^{m} s_{it} z_{it} \tag{31}$$

where S represents the integrated appropriateness of the overall ranking of the alternatives.

The programming should satisfy the following constraints:

$$z_{it} = \begin{cases} 1, \text{if the i-th alternative has been ranked at the t-th position} \\ 0, \text{if the i-th alternative has not been ranked at the t-th position} \end{cases} \tag{32}$$

where $z_{it}\left(i=1,2,\cdots,m;t=1,2,\cdots,m\right)$ represents the variables for ranking the alternatives.

$$\sum_{t=1}^{m} z_{it} = 1, i = 1,2,\cdots,m \tag{33}$$

Eq.33 means that each alternative can only be put in one position.

$$\sum_{i=1}^{m} z_{it} = 1, t = 1,2,\cdots,m \tag{34}$$

Eq.34 means that each position also can only accommodate one alternative.

$$Z = \left\{z_{it}\right\}_{m\times m} \tag{35}$$

Eq.35 represents the decision matrix which is comprised by 0 and 1, and the final priority sequence of these alternatives can be determined by Eq.35.

4. Case study

In order to illustrate the developed method for sustainability prioritization of energy storage technologies, five technologies for energy storage were studied in this section, and they are pumped hydro (PH), compressed air (CA), Lead-Acid (LA), Lithium-ion (LI), and Flywheel (FW). The ten criteria in these four categories developed in Section 2 were all employed to evaluate the sustainability of these five energy storage technologies. The information of the five technologies with respect to the ten evaluation criteria was collected from literatures (Díaz-González, 2012; Ashby and Polyblank, 2012; Chen et al., 2009; Beaudin et al., 2010) and summarized in Table 4. Note that some data of the five technologies with respect to the soft criteria (maturity and environmental impact) cannot be obtained directly, and they were described by using linguistic terms.

Table 4: The information of the five technologies

Category	Metrics	Unit	Pumped hydro	Compressed Air	Lead-Acid	Lithium-ion	Flywheel	
	Capital cost	€/kWh	22.5-45	6.5-37.5	148.33-185	900-1300	400-800	Díaz-González, 2012
Economic	Life	years	40-50	35-35	5-15	14-16	20-20	Díaz-González, 2012
	Operating cost	\$/MJ	0.0006-0.0014	0.0001-0.0019	0.0008-0.0028	0.0019-0.0047	0.0008-0.0017	Ashby and Polyblank, 2012
	Energy efficiency	%	69-74	38-39.25	72.5-80	83-83	85-85	Díaz-González, 2012
Performance	Materials intensity	kg/MJ	60-120	2-12	4.5-12	1.5-2.7	17-500	Ashby and Polyblank, 2012
	Energy intensity	$MJ_{embodied}$/MJ	100-200	74-74	110-980	330-580	750-760	Ashby and Polyblank, 2012
	Energy density	Wh/kg	0.5-1.5	30-60	30-50	75-200	10-30	Chen *et al.*, 2009
Technological	Maturity	/	mature	developed/commercial	NO DATA	Demonstration	Demonstration	Beaudin *et al.*, 2010
Environmental	CO_2 intensity	kg/MJ	8-16	5.3-5.3	5-130	19-50	90-100	Ashby and Polyblank, 2012
	Environmental impact	/	large	Moderate/large	NO DATA	moderate	benign	Evans *et al.*, 2012

NLFP was employed to determine the weights of the four categories as well as that of the evaluation criteria in each category, and the relative performances of the five energy storage technologies with respect to maturity and environmental impact. Taking the calculation of the weights of the four categories as an example, and the three steps of NLFP were specified as follows:

Step 1: The users firstly used the linguistic variables to establish pair-wise comparison judgments.

Seven experts of energy storage technologies including two professors from a key public university of China whose research mainly focuses on renewable energy, three PhD candidates of power engineering, and two engineers of electricity storage and transmission technologies were invited to participate in the decision process. For instance, they held the view that the relative importance of 'economic' category compared with the 'performance' category was identified as "weakly important (WI)", so "WI" was put in cell (1, 2) in the comparison judgments.

Table 5: The pair-wise comparison judgments by using linguistic variables and triangular fuzzy numbers

	Economic	Performance	Technological	Environmental
Economic	-	WI	MI	SI
Performance		-	WI	MI
Technological			-	MI
Environmental				-
	Economic	Performance	Technological	Environmental
Economic	-	(1, 2, 3)	(2, 3, 4)	(4, 5, 6)
Performance		-	(1, 2, 3)	(2, 3, 4)
Technological			-	(2, 3, 4)
Environmental				-
Weights	0.4592	0.2656	0.1936	0.0816

Step 2: All the linguistic variables used in the pair-wise comparison matrix can be transformed into triangular fuzzy numbers. For instance, the element "WI" in cell (1, 2) of the comparison judgments can be transformed into (1, 2, 3). Similarly, the pair-wise comparison judgments by using triangular fuzzy numbers can be obtained, as presented in Table 5.

Step 3: The programming for determining the weights of the four categories can be obtained, as presented in (36)

$$\begin{aligned}
&\max \quad \lambda \\
&\left(a_{12}^{2}-a_{12}^{1}\right)\lambda\omega_2-\omega_1+a_{12}^{1}\omega_2\le 0 \\
&\left(a_{12}^{3}-a_{12}^{2}\right)\lambda\omega_2+\omega_1-a_{12}^{3}\omega_2\le 0 \\
&\left(a_{13}^{2}-a_{13}^{1}\right)\lambda\omega_3-\omega_1+a_{13}^{1}\omega_3\le 0 \\
&\left(a_{13}^{3}-a_{13}^{2}\right)\lambda\omega_3+\omega_1-a_{13}^{3}\omega_3\le 0 \\
&\left(a_{14}^{2}-a_{14}^{1}\right)\lambda\omega_4-\omega_1+a_{14}^{1}\omega_4\le 0 \\
&\left(a_{14}^{3}-a_{14}^{2}\right)\lambda\omega_4+\omega_1-a_{14}^{3}\omega_4\le 0 \\
&\left(a_{23}^{2}-a_{23}^{1}\right)\lambda\omega_3-\omega_2+a_{23}^{1}\omega_3\le 0 \\
&\left(a_{23}^{3}-a_{23}^{2}\right)\lambda\omega_3+\omega_2-a_{23}^{3}\omega_3\le 0 \\
&\left(a_{24}^{2}-a_{24}^{1}\right)\lambda\omega_4-\omega_2+a_{24}^{1}\omega_4\le 0 \\
&\left(a_{24}^{3}-a_{14}^{2}\right)\lambda\omega_4+\omega_2-a_{24}^{3}\omega_4\le 0 \\
&\left(a_{34}^{2}-a_{34}^{1}\right)\lambda\omega_4-\omega_3+a_{34}^{1}\omega_4\le 0 \\
&\left(a_{34}^{3}-a_{34}^{2}\right)\lambda\omega_4+\omega_3-a_{34}^{3}\omega_4\le 0 \\
&\sum_{i=1}^{4}\omega_i=1 \\
&\omega_i>0, i=1,2,3,4
\end{aligned} \tag{36}$$

After substituting all the parameters in (36), this non-linear programming can be solved. The optimum value of λ^* equals to 0.3723, it is greater than zero, thus, it can completely satisfy the initial judgments. Therefore, the weights of the four categories can be determined, and they are 0.4592, 0.2656, 0.1936, and 0.0816, respectively.

In a similar way, the local weights of the criteria in each category can also be determined by the NLFP method, and the results were summarized in the Appendix. Then, the global weights of the ten evaluation criteria can be determined by Eq.37. The results were presented in the Appendix.

$$\omega_j^{global} = \omega_j^{local} \times \omega_{category} \tag{37}$$

where ω_j^{global} represents the global weight of the j-th criterion, ω_j^{local} represents the local weight of the j-th criterion, and $\omega_{category}$ represents the weight of the corresponding category.

As mentioned above, the NLFP method was also employed to determine the relative performances of the five energy storage technologies with respect to maturity and environmental impact, and the results were also presented in the Appendix. It is worth pointing out that the data determined by the NLFP method represent the performances of these five energy storage technologies with respect to maturity and environmental impact, thus, both maturity and environmental impact can be recognized as benefit-type criteria. Therefore, there are five cost-type criteria, namely capital cost, operating cost, materials intensity, energy intensity, and CO_2 intensity. Then, the decision-making matrix can be determined (see the Appendix).

The developed interval multi-attribute decision analysis method was employed to determine the sustainability order of these five energy storage technologies. The ranking matrix with respect to each evaluation criterion can be firstly determined. Taking the ranking matrix with respect to capital cost as an example:

The capital costs of pumped hydro (PH), compressed air (CA), Lead-Acid (LA), Lithium-ion (LI), and Flywheel (FW) are [22.5 45], [6.5 37.5], [148.33 185], [900 1300],and [400 800] €/kWh, respectively. According to Eq.24 and Eq.25, all the elements in the possibility matrix for comparing each pair of the energy storage technologies with respect to capital cost can be determined, and the results were summarized in Eq.38.

$$\begin{array}{cccccc} \textit{capital cost} & PH & CA & LA & LI & FW \\ PH & 0.5000 & 0.7196 & 0 & 0 & 0 \\ CA & 0.2804 & 0.5000 & 0 & 0 & 0 \\ LA & 1.0000 & 1.0000 & 0.5000 & 0 & 0 \\ LI & 1.0000 & 1.0000 & 1.0000 & 0.5000 & 1.0000 \\ FW & 1.0000 & 1.0000 & 1.0000 & 0 & 0.5000 \end{array} \tag{38}$$

Similarly, the priority score (PS) of each energy storage technology with respect to capital cost can be determined by Eq.26, and they are 1.2196, 0.7804, 2.5000, 4.5000, and 3.5000, respectively.

However capital cost is a cost-type criterion, thus, the greater the priority score, the worse the corresponding energy storage technology will be. Therefore, the priority order of these five energy storage technologies from the best to the worst is compressed air (CA), pumped hydro (PH), Lead-Acid (LA), flywheel (FW), and Lithium-ion (LI). Based on the priority order, the ranking matrix with respect to capital cost can be determined by Eqs.27-28, and the results were presented in Eq.39.

$$\begin{array}{cccccc} \textit{capital cost} & 1 & 2 & 3 & 4 & 5 \\ PH & 0 & 1 & 0 & 0 & 0 \\ CA & 1 & 0 & 0 & 0 & 0 \\ LA & 0 & 0 & 1 & 0 & 0 \\ LI & 0 & 0 & 0 & 0 & 1 \\ FW & 0 & 0 & 0 & 1 & 0 \end{array} \tag{39}$$

In a similar way, the other nine ranking matrices for comparing each pair of energy storage technologies with respect to the other nine criteria can also be determined, and the results were summarized in the Appendix.

After determining all the ten ranking matrices, the weighted ranking matrix can be obtained by aggregating these ten matrices into a single matrix according to Eqs. 29-30, and the results were presented in Eq.40.

$$\{s_{it}\}_{5\times5} = \begin{array}{cccccc} & 1 & 2 & 3 & 4 & 5 \\ PH & 0.4232 & 0.3034 & 0 & 0.2371 & 0.0363 \\ CA & 0.3034 & 0.4827 & 0.0653 & 0 & 0.1486 \\ LA & 0 & 0 & 0.4377 & 0.3439 & 0.2184 \\ LI & 0.0595 & 0.2139 & 0.2674 & 0.1531 & 0.3061 \\ FW & 0.2139 & 0 & 0.4232 & 0.2659 & 0.0970 \end{array} \quad (40)$$

Then, the programming for determining the priority order of the five energy storage technologies can be stablished, as presented in Eqs.41-45.

$$Max\, S = \sum_{i=1}^{5}\sum_{t=1}^{5} s_{it} z_{it} \quad (41)$$

$$z_{it} = \begin{cases} 1,\text{if the i-th energy storge technology has been ranked at the t-th position} \\ 0,\text{if the i-th energy storage technology has not been ranked at the t-th position} \end{cases} \quad (42)$$

where $z_{it}\left(i=1,2,\cdots,5;t=1,2,\cdots,5\right)$ represents the variables for ranking the five energy storage technologies.

$$\sum_{t=1}^{5} z_{it} = 1, i = 1,2,\cdots,5 \quad (43)$$

$$\sum_{i=1}^{5} z_{it} = 1, t = 1,2,\cdots,5 \quad (44)$$

$$Z = \{z_{it}\}_{5\times5} \quad (45)$$

The results of this programming can be obtained when integrating with Eq.40, and the maximum value of the appropriateness is 1.9791, and the results were presented in Eq.46.

$$\begin{array}{cccccc} capital\ cost & 1 & 2 & 3 & 4 & 5 \\ PH & 1 & 0 & 0 & 0 & 0 \\ CA & 0 & 1 & 0 & 0 & 0 \\ LA & 0 & 0 & 0 & 1 & 0 \\ LI & 0 & 0 & 0 & 0 & 1 \\ FW & 0 & 0 & 1 & 0 & 0 \end{array} \quad (55)$$

According to the results, it could be concluded that pumped hydro (PH) was ranked in the first position, followed by compressed air (CA), flywheel (FW), Lead-Acid (LA), and Lithium-ion (LI) according to their sustainability performances**.** It is worth pointing out that the developed multi-attribute sustainability ranking framework is a generic method, and it can be popularized to some other cases. In other words, although there are merely five alternatives for energy storage with the considerations of only ten sustainability criteria in this case, the users can adopt this method for sustainability ranking of some other alternative energy storage technologies with the considerations of more criteria for sustainability assessment.

5. Discussion

The performances (integrated weights) of the five energy storage technologies with respect to each of the four categories (economic, performance, technological, and environmental) can also be determined according to Eqs.29-30, and the results were presented in Figure 3. The integrated weights of the five energy storage technologies can be recognized as the supporting degree of ranking these alternatives in the corresponding positions according to their relative performances on each category. It is worth pointing out that the performances (integrated weights) of the five energy storage technologies with respect to each of the four categories were determined by Eqs.29-30 by incorporating all the criteria in the corresponding category. For instance, all the three criteria including capital cost, life, and operating cost were integrated to determine the performances (integrated weights) of the five energy storage technologies with respect to economic category.

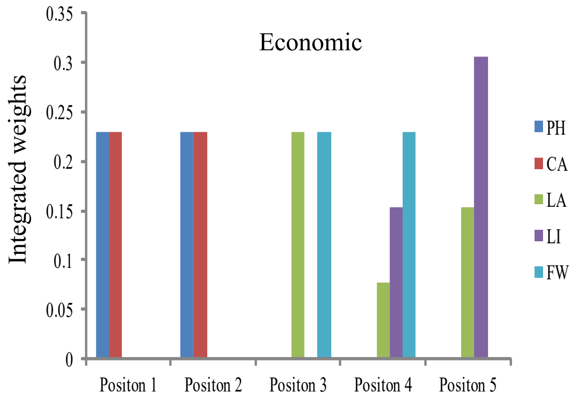

Figure 1(a)

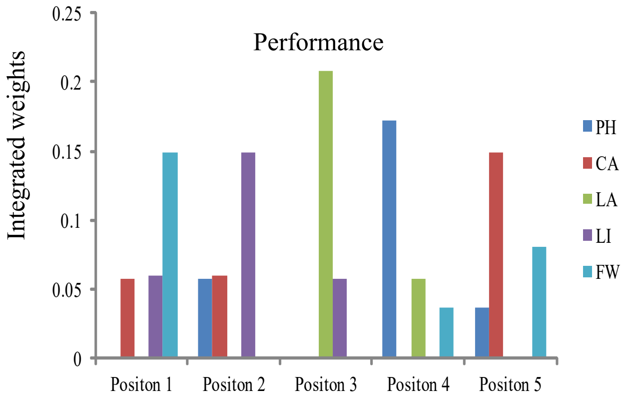

Figure 1(b)

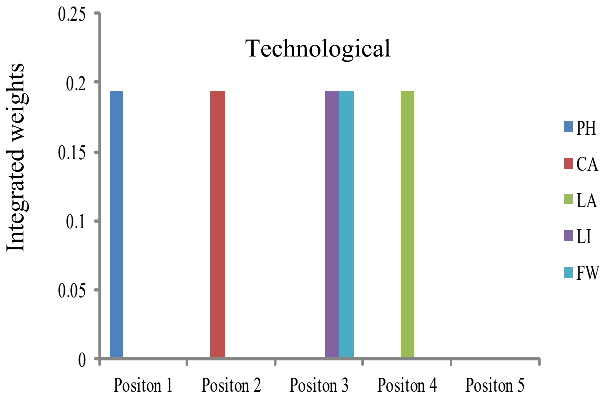

Figure 1(c)

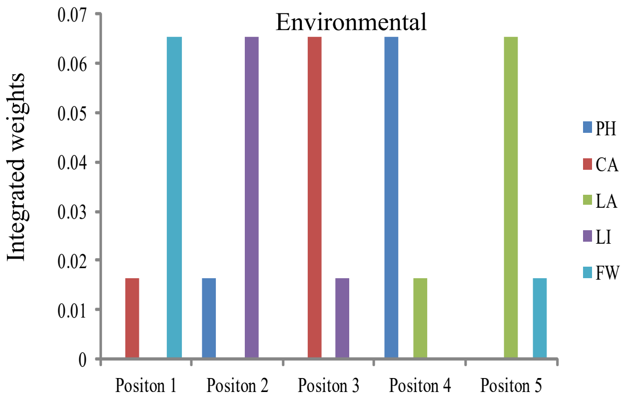

Figure 1(d)

Figure 3: The performances of the five energy storage technologies

In order to investigate the robustness of the sustainability ranking of the five energy storage technologies determined by the development interval multi-attribute decision analysis method, sensitivity analysis was carried out by altering the relative importance of the ten criteria for sustainability assessment of energy storage technologies, and the following twelve cases have been studied:

Base case: use the weights determined by NLFP to determine the sustainability ranking of the five energy storage technologies;

Case 1: assign all the ten evaluation criteria with an equal weight-0.1000 to determine the sustainability ranking of the five energy storage technologies;

Case 2-11: assign a dominant weight (0.3700) to each of the ten criteria, and assign the other nine criteria with an equal weight (0.0700). For instance, 0.3700 was assigned to capital cost, and the other nine criteria were assigned an equal weight (0.07).

The results of sensitivity analysis were presented in Table 6. It is apparent that altering the weights of the ten criteria will significantly influence the sustainability ranking of the five energy storage technologies, and the sustainability ranking was highly dependent on the weights of the criteria. However, the holistic trend is that pumped hydro and compressed air are the most sustainable scenarios for energy storage.

Table 6: The results of sensitivity analysis

	Pumped hydro	Compressed Air	Lead-Acid	Lithium-ion	Flywheel
Base case	1	2	4	5	3
Case 1	1	2	4	3	5
Case 2	2	1	3	5	4
Case 3	1	2	3	4	3
Case 4	1	2	4	5	3
Case 5	4	5	3	2	1
Case 6	4	2	3	1	5
Case 7	2	1	4	3	5
Case 8	1	2	3	1	4
Case 9	1	2	4	3	5
Case 10	2	1	4	3	5
Case 11	4	3	5	2	1

In order to validate the results determined by the developed multi-attribute decision analysis method, the interval TOPSIS method (Yue, 2011; Yue 2012) was also employed to rank the five energy storage technologies, and the results determined by the interval TOPSIS are the same to that determined by the proposed method in this study. To some extent, it could be concluded that pumped hydro and compressed air are the two best energy storage technologies in current stage.

6. Conclusion

The objective of this study is to develop a method for sustainability prioritization of energy storage technologies, a criteria system which consists of ten criteria in four categories were developed for sustainability assessment of energy storage technologies. The NLFP method based on fuzzy set theory was employed to determine the weights of the evaluation criteria for sustainability prioritization of energy storage technologies, and a novel interval multi-attribute decision analysis was developed for ranking the energy storage technologies under uncertainties. The developed method has the following two strengths:

(1) The users are allowed to use linguistic terms which correspond to triangular fuzzy numbers to establish the pair-wise comparison judgements for determining the weights of the evaluation criteria, and the users do not need to establish the complete comparison matrix;

(2) The developed interval multi-attribute decision analysis can rank the alternative energy storage technologies under uncertainties

However, all the ten criteria for sustainability ranking of energy storage technologies are assumed to be independent in this study. Actually, this assumption neglected the consideration of the dependences and interactions among these evaluation criteria. Accordingly, the weights determined under this assumption are not accurate and cannot accurately reflect the preferences and opinions of the decision-makers. The future work of the authors is to develop a novel weighting method by combing NLFP method and the thoughts of Analytic Network Process (ANP) to determine the weights of the evaluation with the consideration of the dependences and interactions among these evaluation criteria.

Appendix

Table A1: The local weights of the criteria in each category determined by the NLFP method

Economic	Capital cost	Life	Operating cost	
Capital cost	-	(1, 2, 3)	(3, 4, 5)	
Life		-	(2, 3, 4)	
Operating cost			-	
Weights	0.5000	0.3333	0.1667	
Performances	Energy efficiency	Materials intensity	Energy intensity	Energy density
Energy efficiency	-	(5, 6, 7)	(2, 3, 4)	(3, 4, 5)
Materials intensity		-	(1/4, 1/3, 1/2)	(1/3, 1/2, 1)
Energy intensity			-	(1, 2, 3)
Energy density				-
Weights	0.5595	0.0872	0.2165	0.1367
Technological	CO_2 intensity	Environmental impact		
CO_2 intensity	-	(1/6, 1/5, 1/4)		
Environmental impact		-		
Weights	0.2000	0.8000		

Table A2: The global weights of the ten criteria for sustainability assessment of energy storage technologies

Category	Weights	Criteria	Local weights	Global weights
		Capital cost	0.5000	0.2296
Economic	0.4592	Life	0.3333	0.1531
		Operating cost	0.1667	0.0765
		Energy efficiency	0.5595	0.1486
	0.2656	Materials intensity	0.0872	0.0232
Performance		Energy intensity	0.2165	0.0575
		Energy density	0.1367	0.0363
Technological	0.1936	Maturity	1	0.1936
Environmental	0.0816	CO_2 intensity	0.2000	0.0163
		Environmental impact	0.8000	0.0653

Table A3: The relative performances of the five energy storage technologies with respect to maturity and environmental impact by the NLFP method

Maturity	Pumped hydro	Compressed Air	Lead-Acid	Lithium-ion	Flywheel
Pumped hydro	-	(2, 3, 4)	(5, 6, 7)	(3, 4, 5)	(3, 4, 5)
Compressed Air		-	(2, 3, 4)	(1, 2, 3)	(1, 2, 3)
Lead-Acid			-	(1/3, 1/2,1)	(1/3, 1/2,1)
Lithium-ion				-	(1, 1, 1)
Flywheel					-
Relative performances	0.5008	0.1971	0.0775	0.1123	0.1123
Environmental impact	Pumped hydro	Compressed Air	Lead-Acid	Lithium-ion	Flywheel
Pumped hydro	-	(1/3, 1/2, 1)	(1, 2, 3)	(1/4, 1/3, 1/2)	(1/6, 1/5, 1/4)
Compressed Air		-	(2, 3, 4)	(1/3, 1/2, 1)	(1/4, 1/3, 1/2)
Lead-Acid			-	(1/6, 1/5, 1/4)	(1/8, 1/7, 1/6)
Lithium-ion				-	(1/3, 1/2, 1)
Flywheel					-
Relative performances	0.0941	0.1525	0.0583	0.2660	0.4291

Table A4: The decision-making matrix

Category	Metrics	Unit	Pumped hydro	Compressed Air	Lead-Acid	Lithium-ion	Flywheel	Weights
Economic	Capital cost	€/kWh	22.5-45	6.5-37.5	148.33-185	900-1300	400-800	0.2296
	Life	years	40-50	35-35	5-15	14-16	20-20	0.1531
	Operating cost	$/MJ	0.0006-0.0014	0.0001-0.0019	0.0008-0.0028	0.0019-0.0047	0.0008-0.0017	0.0765
Performance	Energy efficiency	%	69-74	38-39.25	72.5-80	83-83	85-85	0.1486
	Materials intensity	kg/MJ	60-120	2-12	4.5-12	1.5-2.7	17-500	0.0232
	Energy intensity	$MJ_{embodied}/MJ$	100-200	74-74	110-980	330-580	750-760	0.0575
	Energy density	Wh/kg	0.5-1.5	30-60	30-50	75-200	10-30	0.0363
Technological	Maturity	/	0.5008	0.1971	0.0775	0.1123	0.1123	0.1936
Environmental	CO_2 intensity	kg/MJ	8-16	5.3-5.3	5-130	19-50	90-100	0.0163
	Environmental impact	/	0.0941	0.1525	0.0583	0.2660	0.4291	0.0653

Table A5: The ranking matrices

Life	1	2	3	4	5	Operating cost	1	2	3	4	5	Energy Efficiency	1	2	3	4	5
PH	1	0	0	0	0	PH	1	0	0	0	0	PH	0	0	0	1	0
CA	0	1	0	0	0	CA	0	1	0	0	0	CA	0	0	0	0	1
LA	0	0	0	0	1	LA	0	0	0	1	0	LA	0	0	1	0	0
LI	0	0	0	1	0	LI	0	0	0	0	1	LI	0	1	0	0	0
FW	0	0	1	0	0	FW	0	0	1	0	0	FW	1	0	0	0	0
Materials intensity	1	2	3	4	5	Energy intensity	1	2	3	4	5	Energy density	1	2	3	4	5
PH	0	0	0	1	0	PH	0	1	0	0	0	PH	0	0	0	0	1
CA	0	1	0	0	0	CA	1	0	0	0	0	CA	0	1	0	0	0
LA	0	0	1	0	0	LA	0	0	0	1	0	LA	0	0	1	0	0
LI	1	0	0	0	0	LI	0	0	1	0	0	LI	1	0	0	0	0
FW	0	0	0	0	1	FW	0	0	0	0	1	FW	0	0	0	1	0
Maturity	1	2	3	4	5	CO_2 intensity	1	2	3	4	5	Environmental impact	1	2	3	4	5
PH	1	0	0	0	0	PH	0	1	0	0	0	PH	0	0	0	1	0
CA	0	1	0	0	0	CA	1	0	0	0	0	CA	0	0	1	0	0
LA	0	0	0	1	0	LA	0	0	0	1	0	LA	0	0	0	0	1
LI	0	0	1	0	0	LI	0	0	1	0	0	LI	0	1	0	0	0
FW	0	0	1	0	0	FW	0	0	0	0	1	FW	1	0	0	0	0

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