Sustainable evaluation of energy storage technologies for wind power generation: A multistage decision support framework under multi-granular unbalanced hesitant fuzzy linguistic environment

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Sustainable evaluation of energy storage technologies for wind power generation: A multistage decision support framework under multi-granular unbalanced hesitant fuzzy linguistic environment

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ABSTRACT

Energy storage technology (EST) plays a foundational role for dealing with the intermittency of wind power and accelerating the structural revolution of renewable energy systems. Generally, EST selection is treated as a multiple-criteria group decision-making problem. However, stakeholders are not allowed to express multiple preferences via personalized linguistic distribution assessment and their risk appetites have received less attention in the existing approaches. This study aims at prioritizing ESTs by developing a novel multistage support framework where multi-granular unbalanced hesitant fuzzy linguistic term sets (UHFLTSs) are adopted to depict and quantify stakeholders' opinions based on personalized semantics and granularities. A sustainable index system is devised in four dimensions (economic, technical, environmental and social) and the extended best-worst method (BWM) under multi-granular UHFLTSs environment is combined with maximum deviation method to determine the hybrid weights of criteria. A novel approach linking multi-granular UHFLTSs with double parameters TOPSIS method integrating risk appetite and optimism preference of stakeholders is further proposed by constructing optimization model, which can simultaneously yield the credible experts' weights and prioritize the most desirable technology. The application of the proposed framework is demonstrated through an empirical case. Eventually, sensitivity analysis and comparative analysis are implemented to verify the effectiveness and validity of our proposal.

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Keywords: Energy storage technology; Multi-granular unbalanced hesitant fuzzy linguistic information; Multi-criteria group decision making; Best-worst method; Double parameters TOPSIS.

1. Introduction

In the past few decades, heavy dependence on fossil fuels and enormous energy consumption have constantly deepened the environmental pollution and carbon emissions. Exploiting the renewable energy sources (solar power, wind power, hydropower, geothermal energy and tidal energy) has been regarded as a promising way to alleviate the environmental pressure and improve energy security [1], providing the universal access to affordable, reliable and modern energy services. Compared to other renewable energy sources, i.e. hydropower, wind power at scale is relatively advanced and is growing quickly all over the world as shown in Fig. 1. In 2019, wind generated around 5% of global electricity and 2% of global energy. The cumulative wind power installation of the world reached 733.28 GW in 2020. Fig. 2 presents the installed wind energy capacity globally in 2020 [2]. As an effective provider of renewable energy, onshore wind resources are rich in northwest China, where wind outputs can be converted into electricity at a lower cost and greater convenience [3]. Electric power produced by the large-scale wind farms constructed in northwest China needs remotely transmitting to the southeast and central China over thousands of kilometers before consumption. However, owing to the stochastic nature of wind power, the output fluctuations and intermittency can cause significance obstacles of being integrated into the power grids undertaking the far-away delivery [4]. To avoid the curtailment of wind energy and economic losses in such situation, the power generated should be utilized or stored in time [3]. In this regard, energy storage technologies (ESTs) as ancillary services of power system can smooth wind power variation with great efficiency and enlarge the benefits of power grid enterprise [5].

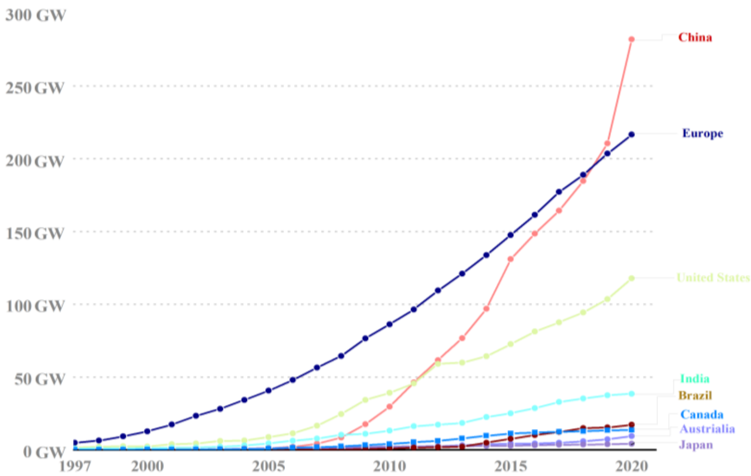


Fig. 1. Cumulative installed wind energy capacity of countries across the world from 1997-2020.

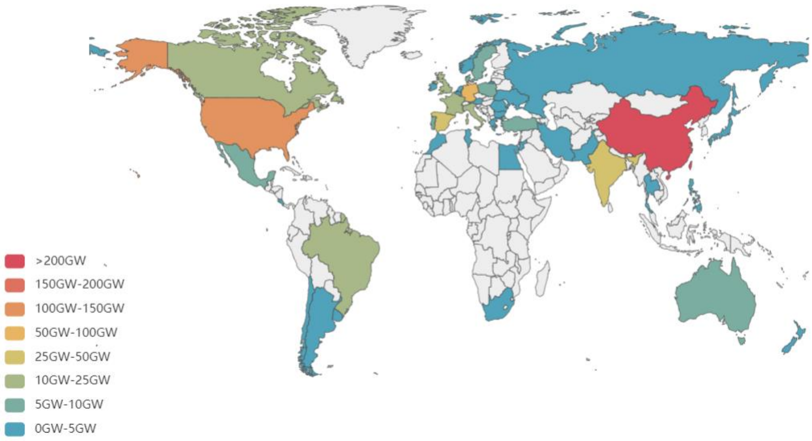


Fig. 2. Installed wind energy capacity in 2020 measured in gigawatts (GW).

As discussed above, energy storage as underpinning technology can realize the controllability of highly erratic and intermittent wind power source and facilitate long-distance and large-scale transmission. In response to these technological necessities, various ESTs have been developed i.e., flywheel, capacitors, pumped hydro, compressed air, lead acid battery, high temperature batteries and flow batteries, etc., and they possess different characteristics and performances i.e., energy intensity, maturity, storage capacity, lifetime and power rating, etc. Accordingly, it is a complex task for enterprise to evaluate the overall performance of the available ESTs when confronting with diverse conflicting qualitative and quantitative criteria associated with multiple perspectives. The evaluation process can be summarized as criteria selection-preference collection-EST prioritization, namely multiple stakeholders from different sectors to evaluate available ESTs respect to the considered criteria and further prioritize the most desirable EST based on the collective performances. Thus, it is straightforward that the selection of ESTs can be perceived as a multi-criteria group decision-making (MCGDM) problem [6-8]. To date, most of current studies on exploring MCGDM methods to sort or prioritize alternative ESTs generally employ a type of uniformed information in the form of crisp number or single linguistic term to express the preferences. Actually, decision makers (DMs) /stakeholders are difficult to provide their assessments with only one type of uniformed linguistic formation which cause information loss to some extent. Considering the vagueness of human cognition and complexity of EST selection issue, it is reasonable that stakeholders need to be provided with more elaborated expressions when delivering their evaluation information [9]. Recently, multi-granular unbalanced hesitant fuzzy linguistic term set (UHFLTS) where linguistic terms are not uniformly and symmetrically distributed on differential granularities of individuals are commonly used to characterizing stakeholders' opinions [10] for the superiority of being closer to human beings' cognition. Moreover, EST evaluation is a complicated process involved by many interactive criteria that should be assigned with different weights to signify the relative significance degree. BWM [11] considers to be a pragmatic and promising technique in deriving the relative weights of criteria [12] and reducing the number of pairwise comparisons and the inconsistency in DMs' opinions compared to the analytical hierarchy process (AHP), which can enhance the reliability of obtained weights [13, 14]. Whereas, to our best knowledge, BWM with uncertain cognitive linguistic information representation has received less attention, especially in form of multi-granular UHFLTSs. Thus, it is significant to extend BWM under multi-granular UHFLTSs environment for the sake of reducing the onerous computation and handling uncertainty when deriving the comprehensive criteria weights. Furthermore, the increasing complexity of the EST selection demands multiple stakeholders of various domains. Thus, the stakeholders' weights play a key role in the procedure of information aggregation. While numerous approaches have been put forward to derive the stakeholders' weights, for instance the similarity measure [15], the entropy method [16], the clustering method [17], few studies have investigated stakeholders' weights under multi-granular UHFLTSs environment from the perspective of closeness optimization model. As for prioritizing the ESTs, stakeholders may have different risk appetites and optimism preference towards alternative solutions owing to their different backgrounds and stances. Double parameters technique for order preference by similarity to an ideal solution (TOPSIS), an improved alternative ranking method developed by Xian et al. [18], has been demonstrated with advantages of easy implementation and excellent depiction of the psychological characteristic of DMs, compared with other ranking methods like classical TOPSIS, simple additive weighting (SAW), VIsekriterijumska Optimizcija I Kompromisno Resenje (VIKOR) and combinative distance-based assessment (CODAS). Hence, it is realistic to extend the original double parameters TOPSIS into a fuzzy linguistic environment, which can reflect ambiguity and uncertainty of decision making and consider the stakeholders' psychological characteristic, thereby reducing decision risk.

Motivated by the aforementioned truth, it is worthwhile to investigate a multistage decision support framework to satisfy these distinct requirements for EST evaluation. To that end, this paper takes the advantage of the powerful representation capability of multi-granular UHFLTSs with the combined weighting approach based on double parameters TOPSIS method to propose a novel multistage MCGDM decision support framework to prioritize ESTs for wind power. Overall, the contribution of this study to contrive a multistage EST evaluation framework stems from the following three aspects:

(1) To facilitate the evaluation of ESTs, a sustainable indicator system is established from a holistic perspective with economic, social, technical and environment dimensions involved. Then a novel multi-granular UHFLTSs-based MCGDM method is proposed to conduct complicated ESTs evaluation under the multiexpert, multicriteria, multigranular and multipreference scenario, where experts are allowed to represent personalized preferences towards the optional ESTs and relative importance of criteria in virtue of individual semantics and granularities, effectively alleviating the experts' cognitive burden in the EST evaluation procedure.

(2) To derive the appropriate criteria weights considering people's vacillation and hesitation adequately in the face of choice, we extend classic BWM method with multi-granular UHFLTSs information. The weight information for criteria is further distinguished by the combination of UHFLTS-BWM and maximum deviation method. Subjective and objective weights are joint to empower the differentiated importance of criteria. This criteria weight determination approach provides a beneficial reference for fusing multiple preferences in EST selection problems.

(3) To rationalize the EST evaluation process, an innovative approach of deriving experts' weights by extending double parameters TOPSIS into multi-granular UHFLTSs environment is presented considering the risk appetite of stakeholders. A mathematical optimization model constructed by calculating the relative closeness degree towards ideal solutions can

simultaneously derive the optimal stakeholders' weights and prioritize the alternative ESTs referring to the relative closeness degree. The influence of the risk appetite and optimism preference of stakeholders on the outcomes has further investigated through the sensitivity analysis and intuitively presented.

The remainder of this study is structured as follows: Section 2 introduces a literature survey on ESTs evaluation. Motivated by review and analyses, an indicator system of ESTs with sustainability dimensions for wind power is constructed subsequently. Section 3 reviews some basic concepts related to HFLTSs, linguistic distribution assessment (LDA). Section 4 proposes a novel multistage MCGDM framework for EST selection of wind power on extended double parameters TOPSIS approach under multi-granular UHFLTSs environment. An illustrative case, which includes seven ESTs, has been studied by the proposed framework in Section 5. Sensitivity and comparative analysis are performed to verify the reliability and feasibility of the proposed method in Section 6. Conclusions are provided in Section 7.

2. Literature review

In this section, the extant researches related to the EST selection are introduced. Index system of evaluation criteria will be established based on relevant reviews and analyses.

2.1. Energy storage technology selection methods

Throughout the literatures, there are plenty of researches exploring distinct approaches to select superior ESTs for sustainable energies. The related works can be roughly classified into four aspects: (1) Derive the weights of criteria, such as: fuzzy analytic hierarchy process (AHP) [1, 6, 19-24], BWM method [25, 26]. (2) Employ the integrated approaches to handle the EST(s) selection problem, such as: fuzzy-AHP and linear normalization based fuzzy grey relational analysis [22], intuitionistic fuzzy multi-objective optimization by ratio analysis plus the full multiplicative form (MULTIMOORA) [27], the integration of MCDM model and extended Stepwise Weight Assessment Ratio Analysis (SWARA)/Additive Ratio Assessment (ARAS) hybrid computational method [28], and Dombi weighted geometric averaging and multi-attribute ideal-real comparative analysis (MAIRCA) model [29]. (3) Adopt different forms of evaluation information, such as: fuzzy sets [19, 30], intuitionistic fuzzy sets [1], interval numbers [31], type-2 fuzzy sets [23], hesitant fuzzy sets [6, 24], dual hesitant Pythagorean fuzzy linguistic terms [7], and trapezoidal neutrosophic fuzzy numbers (TrNN) [29]. (4) Apply the compromise-ranking method to rank-order alternative ESTs, such as: fuzzy TOPSIS [6,23,30,32], VIKOR [24, 26], CODAS [1], and MULTIMOORA [27].

Table 1 summarizes the previous studies concerning the relevant topics and various techniques utilized by different authors.

Table 1

Summary of prior studies on ESTs.

Technique & Modeling used	Research goals	Authors
Interval numbers-Non-Linear fuzzy prioritization	To sustainably prioritize five ESTs against four major dimensions of sustainability and ten sub-criteria	Ren and Ren [31]
Intuitionistic fuzzy sets-AHP-CODAS	To evaluate the sustainability of four alternative ESTs against nine criteria in four categories	Ren [1]
Type-2 fuzzy sets-AHP-TOPSIS	To select the most suitable EST through a hierarchical structure of sustainability containing four major indicators and 18 sub-criteria	Özkan et al. [23]
Fuzzy TOPSIS	To contrast various heat transfer fluids (HTF) in terms of using a molten salt against ten criteria in concentrated solar power (CSP) systems	Cavallaro [30]
Fuzzy sets-AHP, fuzzy multi-rules and multi sets	To assess the operation of five energy storage systems through investigating eight main indicators	Barin et al. [19]
Fuzzy TOPSIS	To compare and rank five energy storage alternatives for industrial facilities	Ak and Ağlan [32]
Fuzzy Delphi method, AHP and fuzzy consistent matrix	To appraise the energy storage systems in the light of investors and public benefits in the Pacific Northwest region of the United States against 3 major indicators and 13 sub-criteria	Daim et al. [20]
Fuzzy AHP and fuzzy GRA	To pick out the optimal hydrogen energy storage approach for Turkey against five criteria	Gumus et al. [22]
Weighted sum method (WSM) and the sustainable indicator system approach	To compare the sustainability of three energy storage systems storing renewable energy source of intermittence (solar photovoltaic)	Raza et al. [33]
Fuzzy AHP	To appraise five hydrogen storage systems for automobiles against eight criteria in Korea	Gim and Kim [21]
Multi-objective optimization	To find the optimum EST(s) by incorporating comprehensive technical, economic and environmental assessment with multi-	Li et al. [34]

	objective model	
MULTIMOORA-IFN2	To evaluate the sustainability of fourteen ESTs regarding eleven sub-criteria in three main dimensions	Zhang et al. [27]
Fuzzy Delphi, BWM, the entropy method and grey cumulative prospect theory (GCPT)	To priority the battery energy storage systems for micro-grid demonstration projects against five main criteria and 15 sub-criteria	Zhao et al. [25]
Fuzzy Delphi, BWM, the entropy method and VIKOR	To sort out the most desirable battery energy storage system for wind-photovoltaic-energy against 23 sub-criteria of three dimensions	Zhao et al. [26]
Multi-Attribute Value Theory (MAVT)	To rank six potential energy storage projects in Cornwall against the seven attributes identified from stakeholder feedback	Murrant and Radcliffe [35]
Dual hesitant Pythagorean fuzzy linguistic terms-Grey incidence analysis	To select a renewable EST against four main evaluation dimensions and ten sub-criteria in Jiangsu Province, China.	Liu and Du [7]
Trapezoidal neutrosophic fuzzy numbers (TrNN) combined Dombi and MAIRCA model	To assess and prioritize six ESTs in Romania regarding 13 criteria in 4 categories	Pamucar et al. [29]
SWARA and ARAS	To sustainably appraise the performance of seven ESTs regarding five main indicators and seventeen sub-criteria	Albawab et al. [28]
Delphi, HF-AHP and HF-VIKOR	To assess nine ESTs for Turkey regarding four major indicators and nineteen sub-criteria	Çolak and Kaya [24]
HF-AHP and HF-TOPSIS	To comprehensively analysis and assess the sustainable performance of five ESTs in communities and cities regarding four major indicators and fourteen sub-criteria	Acar et al. [6]
Interval fuzzy number based PROMETHEE- II	To select the most promising renewable energy with energy storage portfolio from the aspects of energy generation, transmission on and terminal application.	Wu et al. [36]

Even though the previous techniques and models of the relevant studies are beneficial for coping with ESTs selection problem, some challenges remain to be tackled. The current studies concerning ESTs selection issue usually assume that the stakeholders' perspectives are generally described by crisp numbers or simple linguistic terms under the uniform linguistic measurement sets. However, there is a fact that the same word could mean different meanings for different people [37]. For instance, when evaluating the performance of technologies, three experts think the performance of a technology is ‘at least slightly good’, but the term ‘at least slightly good’ has different semantics for each individual according to their psychological expectations. Moreover, using the same granularity of linguistic measurement sets fails to reveal the heterogeneity of experts with differential knowledge and uncertainty degree [38]. To manage these issues, multi-granular UHFLTS provides different linguistic labels, asymmetrically distributed and consecutive linguistic terms to quantify stakeholders’ opinions, which is more flexible than other linguistic presentations. Plentiful scholars have proven that multi-granular UHFLTS is a more flexible, humanistic and practical uncertain description from the theoretical perspective [38-41]. As the practical concern, a comprehensive consensus measure is developed under multi-granular UHFLTSs environment on sorting the hospital service quality [38]. The practical application of multi-granular UHFLTSs in other fields remains to be explored. Therefore, our approach focuses on the EST sustainable evaluation problem where stakeholders employ multi-granular UHFLTSs by personalizing individual semantics and granularities with great flexibility to provide preferences. This is the first motivation of this paper.

Apart from the necessity of employing the diverse linguistic expressions, another core problem is how to determine the importance degree of criteria. It is observed that AHP is a commonly used technique adopted to generate subjective criteria weights of EST evaluation issues. Whereas, the BWM requires fewer pairwise comparisons than the AHP method and provides more consistent results. Several uncertain information representations have been incorporated with BWM. For instance, Guo and Zhao [42] developed a fuzzy extension of BWM by using triangular fuzzy numbers. Mou et al. [43] addressed the BWM extension with intuitionistic multiplicative sets. Liao et al. [44] proposes the hesitant fuzzy linguistic BWM and provides a novel inconsistency repairing method. BWM is also extended to the probabilistic linguistic context to determine the weights of criteria information by Ming et al. [45]. Nevertheless, up to now, cognitive linguistic information, especially in the form of multi-granular UHFLTSs can not be tackled as inputs of BWM. To provide a comprehensive weight allocation approach, BWM and maximum deviation method are combined under multi-granular UHFLTSs environment. This is the second motivation of this study. Section 4.2 and 4.3 would achieve this objective.

As for the prioritization method, the aforementioned studies make important contributions to managing MCGDM problems, while they cannot effectively depict the risk appetites of stakeholders. To fill this gap, double parameters TOPSIS method is introduced to prioritize available ESTs. Since proposed, double parameters TOPSIS has been extended into uncertain environments to meet the requirements of imprecise assessments, such as intuitionistic Z-linguistic set [18], hesitant fuzzy linguistic term set [46]. However, uncertain double parameters TOPSIS has never been investigated under multi-granular UHFLTSs. In comparison with the existing work, this study innovatively constructs an optimization model to derive the DMs' weights and prioritization of ESTs from the perspectives of relative closeness degree, which considers both preference of alternatives and optimism of DMs. This is the third motivation of our proposal. Section 4.4 would solve this issue.

2.2. Index system for sustainable assessment on energy storage technologies

Typically, the technical characteristics are prominent to certify the suitability of an EST for a specific application since the functionality is a prerequisite [34]. While meeting the technical criteria is of priority for the selection of the suitable EST, sustainability that particularly emphasizes the sustainable development has received extensive attentions in more and more renewable energy industries. Designing the appropriate evaluation index system that integrates the sustainability indicators is critical for identifying the optimal EST for wind farm. Economic, environmental and social perspectives are three pillars of sustainability that need to be incorporated into quantitative decision support methods [47]. Through incorporating the reviews and analyses on previous studies, this paper integrates relevant sustainable perspective into EST evaluation index system, in which a total of twelve criteria in four aspects including economic, environment, technology and society are embedded as shown in Fig. 3.

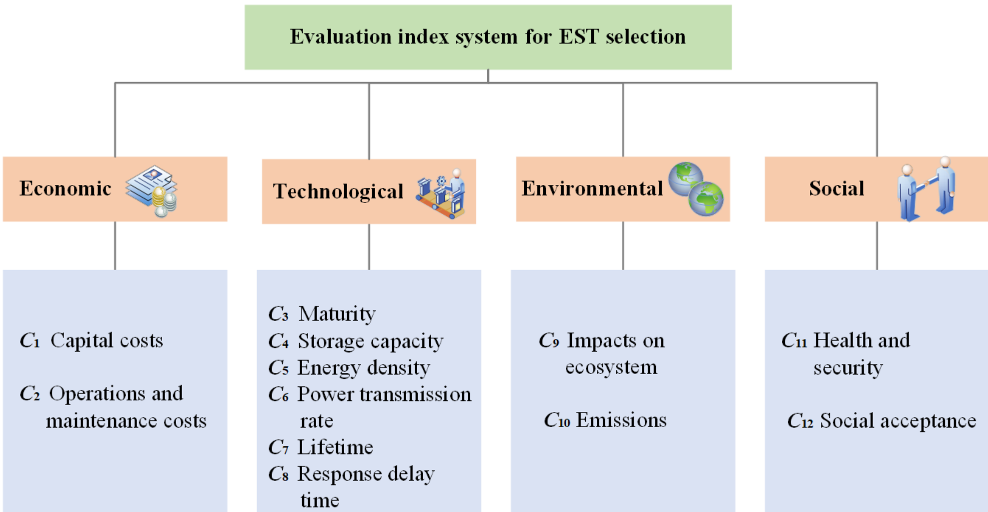


Fig. 3. The sustainable evaluation index system for ESTs.

I *The economic dimension* mainly concerns about the costs associated to equipment, labor, infrastructure, supporting technologies, assistive components and commission from the initial installation to final EST application. The affordability issues impact greatly on the competitiveness of each EST in virtue of economy. The expenditure components investigated are concluded as two criteria: (1) Capital cost; (2) Operations and maintenance costs.

II *The technical dimension* conducts the reliability and energy supply security assessment of ESTs. There mainly exists six criteria in this dimension: (1) Maturity; (2) Storage Capacity; (3) Energy density; (4) Power transmission rate; (5) Lifetime; (6) Response delay time.

III *The environmental dimension* mainly emphasizes the sustainability and the friendliness to the ecological environment. The whole energy storage system may deliver impacts on climate change, human toxicity, water pollution and fossil depletion during the manufacturing, operation, decommissioning and disposal procedure. The evaluation effects are mainly assessed based on two criteria: (1) Impacts on ecosystem; (2) Emissions.

IV *The social dimension* requires to consider the social impacts and public interests since the wind farm is an essential economic and technical asset. The social benefit brought by EST has the indispensable responsibility for improving the well-being of local citizen, and the development of EST should be promoted towards a more sustainable and humane direction. The social impact is mainly investigated based on two criteria: (1) Health and security; (2) Social acceptance. Details of the EST evaluation index system are specifically summarized and explained in Table 2.

Table 2

Detailed description of EST evaluation index system.

Dimension	Criteria	Meaning	Main sources
Economic	Capital costs (C_1)	It refers to the total initial investment costs including the purchase of land, buildings, construction and equipment.	[20, 24, 29, 30]
	Operations and maintenance costs (C_2)	It includes two main parts: the fixed part, rated power and the variable part in terms of its annual discharged energy.	[20, 24, 30, 26]
Technological	Maturity (C_3)	It measures which stage of the energy technology develops to i.e. idea verification, prototype, demonstration and commercialization	[20, 24, 29]
	Storage capacity (C_4)	It indicates the available energy capacity of the storage system	[7, 20, 24, 27]

		after being charged.	
	Energy density (C_5)	It measures the amount of energy stored for a unit of physical size of the storage system.	[7, 24, 27, 33]
	Power transmission rate (C_6)	It measures the ratio of the amount of electricity removed from a storage device to its rated capacity.	[20]
	Lifetime (C_7)	It indicates the period for which the energy storage system can be operating.	[20, 24, 27]
	Response delay time (C_8)	It indicates the interval time between the energy absorption and release of energy storage system.	[7, 20, 27]
Environmental	Impacts on ecosystem (C_9)	It measures the friendliness of energy storage technologies towards ecosystem as the original ecological structure being influenced to some extent.	[7, 24]
	Emissions (C_{10})	It refers to the cost dealing with harmful solid waste, wastewater, waste gas, etc. emitted by energy storage system.	[7, 20, 26]
Social	Health and security (C_{11})	It indicates the condition of employees being protected from what threatens their health and lives under normal operation.	[20, 24, 26]
	Social acceptance (C_{12})	It refers to the degree of public acceptance for the energy storage technologies.	[20, 24]

3. Preliminaries

This section provides some definitions of key concepts used in this paper, such as HFLTS, UHFLTS, distribution assessment of the linguistic term set, and some concepts related to LDA.

Definition 1 *([48])*. Let $S=\{s_0, s_1,..., s_{g-1}\}$ be a finite linguistic term set, an HFLTS H^S on *S* is defined as an ordered subset of consecutive linguistic terms in *S*.

Remark 1. *Clearly, if S is a balanced linguistic term set,* H^S *is called a balanced HFLTS; if S is an unbalanced linguistic term set,* H^S *is called an unbalanced HFLTS.*

Definition 2 *([49])*. Let $S=\{s_0, s_1,\ldots, s_{g-1}\}$ be a finite linguistic term set and $r=\{<s_t,\beta_t> | t=0,1,\ldots,g-1\}$, where $s_t\in S$, $\beta_t\geq 0$, $\sum_{t=0}^{g-1}\beta_t=1$ and β_t is the symbolic proportion of s_t. Then *r* is called a linguistic distribution assessment of the set *S*.

Definition 3 *([49])*. Let $r=\{<s_t,\beta_t>|t=0,1,\dots,g-1\}$ be a linguistic distribution assessment defined on *S*, where $s_t\in S$, $\beta_t\geq 0$ and $\sum_{t=0}^{g-1}\beta_t=1$. The expectation of *r* is defined as follows:

$$E(r)=\sum_{t=0}^{g-1}\beta_t N(s_t), \tag{1}$$

where $N(s_t)=t$ denotes the numerical scale of the linguistic term s_t.

Definition 4 *([15])*. Let $r_1=\{<s_t,\beta_t>|t=0,1,\dots,g-1\}$ and $r_2=\{<s_t,\beta_t>|t=0,1,\dots,g-1\}$ be two linguistic distribution assessments of *S*, then the distance between them is defined as follows:

$$d(r_1,r_2)=\sqrt{\sum_{t=0}^{g-1}[\beta_t N(s_t)-\gamma_t N(s_t)]^2}, \tag{2}$$

where $N(s_t)=t$ denotes the numerical scale of the linguistic term s_t.

Definition 5 *([49])*. Let $\{L_1,L_2,...,L_n\}$ be a set of LDAs defined on *S*, where $L_i=\{<s_t,\beta_t^i>|t=0,1,...,g-1\},i=1,2,...,n$. Let $w=(w_1,w_2,...,w_n)$ be the associated weighting vector of $L_i(i=1,2,...,n)$, satisfying $0\leq w_i\leq 1$ and $\sum_{i=1}^{n}w_i=1$. Then the linguistic distribution assessment weighted averaging (LDAWA) operator is defined as:

$$LDAWA(L_1,L_2,...,L_n)=\{<s_t,\beta_t>|t=0,1,...,g-1\}, \tag{3}$$

where $\beta_t=\sum_{i=1}^{n}w_i\beta_t^i, t=0,1,...,g-1$.

Especially, if $w=(1/n,1/n,...,1/n)$, then the LDAWA operator reduces to the linguistic distribution assessment arithmetic averaging (LDAAA) operator:

$$LDAAA(L_1,L_2,...,L_n)=\{<s_t,\beta_t>|t=0,1,...,g-1\}, \tag{4}$$

where $\beta_t=\frac{1}{n}\sum_{i=1}^{n}\beta_t^i, t=0,1,...,g-1$.

Definition 6 *([50])*. For an LDA decision matrix $R=(r_{ij})_{u\times n}$, the linguistic distribution assessment ideal variate (LDAIV) r^{+} can be defined by Eq. (5).

$$r^{+}=(r_1^{+},r_2^{+},\ldots,r_n^{+}), \tag{5}$$

where $r_j^{+}=\{(s_t,p_{t,j}^{+})\,|\,t=0,1,\ldots,g\}$, and the components of the vector $p_j^{+}=(p_{0,j}^{+},p_{1,j}^{+},\ldots,p_{g,j}^{+})$ can be determined by Eq. (6).

$$p_j^{+}=\begin{cases} p_{0,j}^{+}=0\\ p_{1,j}^{+}=0\\ \quad\vdots\\ p_{k-1,j}^{+}=0\\ p_{k,j}^{+}=1-\sum\limits_{v=k+1}^{g}p_{v,j}^{+}\\ p_{k+1,j}^{+}=\max\limits_{1\le i\le u}\{p_{k+1,ij}\}\\ \quad\vdots\\ p_{g-1,j}^{+}=\max\limits_{1\le i\le u}\{p_{g-1,ij}\}\\ p_{g,j}^{+}=\max\limits_{1\le i\le u}\{p_{g,ij}\} \end{cases} \tag{6}$$

To determine the components of the vector $p_j^{+}=(p_{0,j}^{+},p_{1,j}^{+},\ldots,p_{g,j}^{+})$, we first assign a value to $p_{g,j}^{+}$, i.e., $p_{g,j}^{+}=\max\limits_{1\le i\le u}\{p_{g,ij}\}$, then sequentially assign values to $p_{g-1,j}^{+},\ldots,p_{1,j}^{+}$, $p_{0,j}^{+}$. If $p_{g,j}^{+}+p_{g-1,j}^{+}+\ldots+p_{k+1,j}^{+}<1$ and $p_{g,j}^{+}+p_{g-1,j}^{+}+\ldots+p_{k+1,j}^{+}+\max\limits_{1\le i\le u}\{p_{k,ij}\}\ge 1$, then we take the values of $p_{k,j}^{+}$, $p_{k-1,j}^{+}$ $,\ldots,$ $p_{1,j}^{+}$, $p_{0,j}^{+}$ as follows: $p_{k,j}^{+}=1-\sum\limits_{v=k+1}^{g}p_{v,j}^{+}$, $p_{k-1,j}^{+}=\ldots=p_{1,j}^{+}=p_{0,j}^{+}=0$.

Definition 7 *([50])*. For a linguistic distribution assessment decision matrix $R=(r_{ij})_{u\times n}$, the linguistic distribution assessment nadir variate (LDANV) r^{-} can be defined by Eq. (7).

$$r^{-}=(r_1^{-},r_2^{-},\ldots,r_n^{-}), \tag{7}$$

where $r_j^{-}=\{(s_t,p_{t,j}^{-})\,|\,t=0,1,\ldots,g\}$, and the components of the vector $p_j^{-}=(p_{0,j}^{-},p_{1,j}^{-},\ldots,p_{g,j}^{-})$ can be determined by Eq. (8).

$$\beta_j^- = \begin{cases} p_{0,j}^- = \max\limits_{1\le i\le u}\{p_{0,ij}\} \\ p_{1,j}^- = \max\limits_{1\le i\le u}\{p_{1,ij}\} \\ \vdots \\ p_{\varepsilon-1,j}^- = \max\limits_{1\le i\le u}\{p_{\varepsilon-1,ij}\} \\ p_{\varepsilon,j}^- = 1-\sum\limits_{v=0}^{\varepsilon-1} p_{v,j}^- \\ p_{\varepsilon+1,j}^- = 0 \\ \vdots \\ p_{g-1,j}^- = 0 \\ p_{g,j}^- = 0 \end{cases} \tag{8}$$

To determine the components of the vector $p_j^- = (p_{0,j}^-, p_{1,j}^-, ..., p_{g,j}^-)$, we first assign a value to $p_{0,j}^-$, i.e., $p_{0,j}^- = \max\limits_{1\le i\le u}\{p_{0,ij}\}$, then sequentially assign values to $p_{1,j}^-$, $p_{2,j}^-$,…, $p_{g,j}^-$.

4. Methodology

In this section, we propose a novel multistage MCGDM framework for EST selection problem for wind power. Specifically, this proposed framework consists of four key stages as follows: (1) Describe the problem to be solved and collect the initial evaluation information. (2) Extend BWM into multi-granular UHFLTS environment for deriving subjective criteria weights. (3) Determine the objective criterion weights based on the improved maximizing deviation method under balanced LDA environment. (4) Construct the bi-objective optimization model designed by calculating the distances of alternatives towards ideal solutions to obtain the experts' weights and employ double parameters TOSIS to prioritize ESTs. Fig. 4 summarizes the main stages of the proposed framework for handling EST(s) selection problem.

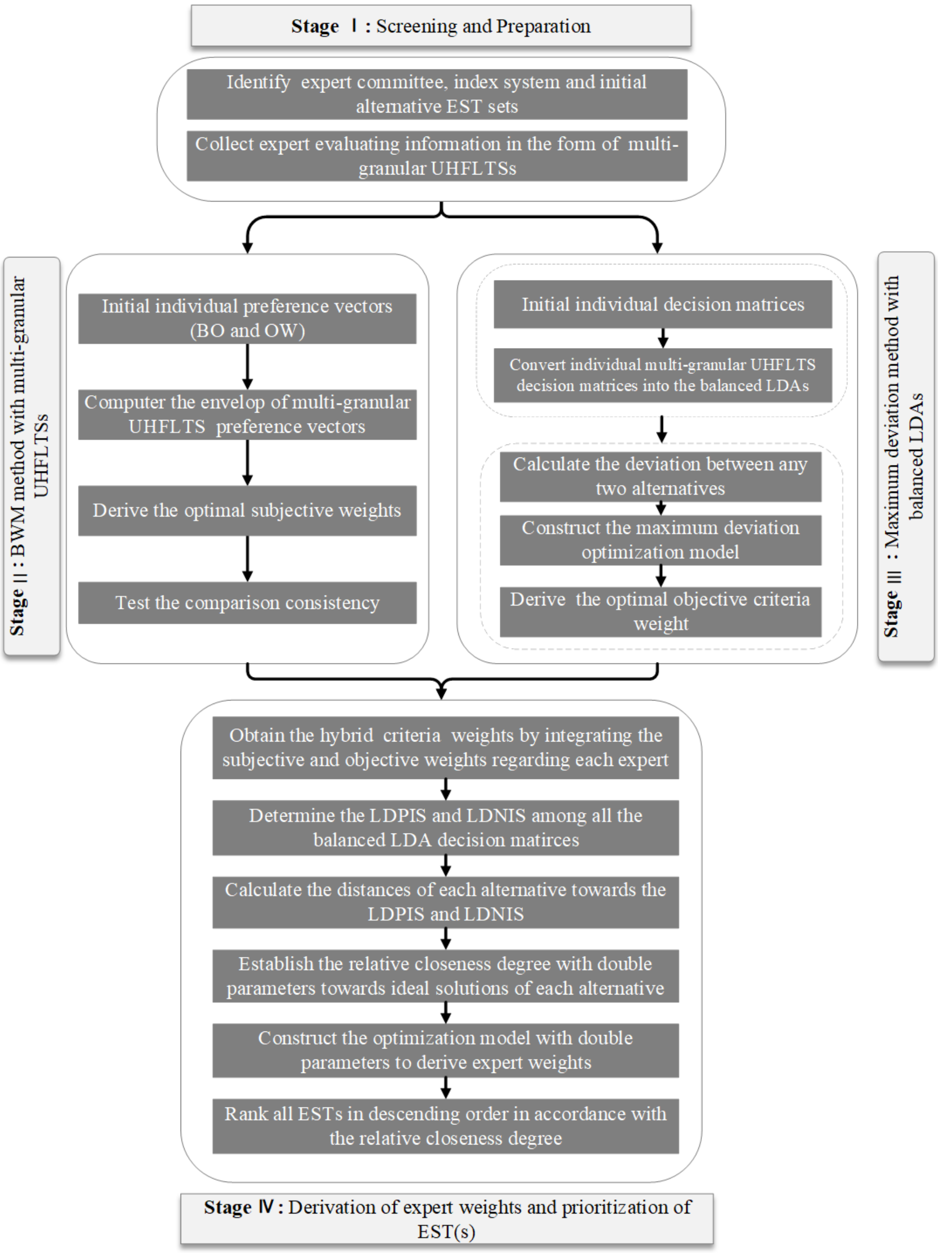


Fig. 4. The flowchart of the proposed decision support framework.

4.1. Stage 1—Describe the decision-making problem under multi-granular UHFLTSs environment and collect the initial evaluation information

Consider a MCGDM problem with the context of hesitant fuzzy linguistic information described as follows. Let $A=\{A_1, A_2, \ldots, A_m\}$ $(m \geq 2)$ be a finite set of alternatives to be evaluated. Let $C=\{C_1, C_2, \ldots, C_n\}$ $(n \geq 2)$ be a finite set of criteria and $E=\{e_1, e_2, \ldots, e_q\}$ $(q \geq 2)$ be a set of experts who participate into the evaluation process.

In order to allow experts to convey their opinions adequately in light of individual preference, differential knowledge and cultural background, we adopt multi-granular UHFLTSs to represent the experts' linguistic expressions in this paper. Let $S^{(l)}=\left\{s_0^l, s_1^l, \ldots, s_{g(l)-1}^l\right\}$ be the unbalanced linguistic term set with the granularity $g(l)$ used by expert e_l, $l=1,2,\ldots,q$. Let $\mathcal{H}^{S^{(l)}}$ be the set of all UHFLTSs defined on $S^{(l)}$. Also, let x_{ij}^l be the hesitant fuzzy evaluation value over alternative A_i with respect to criterion C_j given by expert e_l and we have $x_{ij}^l \in \mathcal{H}^{S^{(l)}}$. Therefore, the decision matrix in the form of UHFLTSs given by lth expert can be constructed as follows:

$$X_{g(l)}^l=(x_{ij}^l)_{m\times n}=\begin{pmatrix} x_{11}^l & x_{12}^l & \cdots x_{1n}^l \\ x_{21}^l & x_{22}^l & \cdots x_{2n}^l \\ \vdots & \vdots & \ddots \vdots \\ x_{m1}^l & x_{m2}^l & \cdots x_{mn}^l \end{pmatrix},\ l=1,2,\ldots,q. \tag{9}$$

4.2. Stage II—Determine subjective criteria weights based on multi-granular UHFLTS-BWM

BWM, proposed by Rezaei [11], is an effective criteria weight determination method that reduces the number of information requested and the inconsistency in the opinions. In this subsection, we extend the classical BWM to multi-granular UHFLTSs environment to derive the subjective criteria weights. Conventionally, after determining the best criterion and worst criterion, experts should pairwise compare the best/worst criterion with all the other criteria by means of crisp numbers using a 1 to 9 scale [51]. Whereas, experts prefer to use linguistic expressions to convey cognitive information instead of crisp numbers when they are not confident with the relative comparison. In our approach, pairwise comparisons are done to establish preference vectors in the form of UHFLTSs. The detailed steps to determine the criteria weight are presented as follows.

Step 1. Determine the best (most important) criterion and the worst (least important) criterion.

According to the index system, the best criterion and the worst criterion are identified by each expert, which are represented as C_B^l and C_W^l $(l=1,2,...,q)$, respectively.

Step 2. Perform the fuzzy reference comparisons.

Given the results of last step, experts are asked to do pairwise comparisons of the best criterion C_B^l over all the other criteria and all the other criteria over the worst criterion C_W^l to obtain the UHFLTSs Best-to-Others preference vector, $H_{BO^l}=\left(h_{B_1^l}, h_{B_2^l}, ..., h_{B_n^l}\right)^T$ and UHFLTSs Others-to-Worst preference vector, $H_{OW^l} = \left(h_{W_1^l}, h_{W_2^l}, \ldots, h_{W_n^l}\right)^T$, where $h_{B_j^l}, h_{W_j^l}\,(j = 1,2,\ldots,n) \in \bar{\mathcal{H}}^{S^{(l)}}$ and $\bar{\mathcal{H}}^{S^{(l)}}$ is the set of all UHFLTSs defined on the unbalanced linguistic term set $\bar{S}^{(l)} = \left\{\bar{s}_0^l, \bar{s}_1^l, \ldots, \bar{s}_{g(l)-1}^l\right\}$.

Step 3. Compute the envelop of UHFLTSs preference vectors by proposing a novel fuzzy envelop approach.

To facilitate the computing with words process, Liu and Rodríguez [52] defined the concept of fuzzy envelope for HFLTS characterized by a trapezoidal fuzzy membership function through the application of OWA operator. Inspired by such work, we propose a novel fuzzy envelop approach for UHFLTS of which linguistic semantics are represented by triangular fuzzy membership function. The output is achieved by integrating the fuzzy membership functions of all the linguistic terms consisting UHFLTS with MSM operator. The general process of the fuzzy envelop for UHFLTS is described as follows.

Let $H_S = \left\{s_i, s_{i+1}, \ldots, s_j\right\}$ be an UHFLTS, all linguistic terms $s_\alpha \in H_S$, $\alpha = i, \ldots, j$ in the UHFLTS are symbolized as triangular fuzzy membership functions $A^\alpha = T(a_L^\alpha, a_M^\alpha, a_R^\alpha), \alpha = 0,1,\ldots,g-1$. Especially, when $g = 9$, the semantics of linguistic terms can be depicted in Fig. 5. Therefore, it is reasonable to integrate all linguistic terms in the UHFLTS H_S.

$$T(H_S) = \left\{a_L^i, a_M^i, a_L^{i+1}, a_R^i, a_M^{i+1}, a_L^{i+2}, a_R^{i+1}, \ldots, a_L^j, a_R^{j-1}, a_M^j, a_R^j\right\}. \tag{10}$$

For the sake of simplicity, a special case $a_R^{k-1} = a_M^k = a_L^{k+1}$ was considered, in which case $T(H_S) = \left\{a_L^i, a_M^i, a_M^{i+1}, \ldots, a_M^j, a_R^j\right\}$ is obtained.

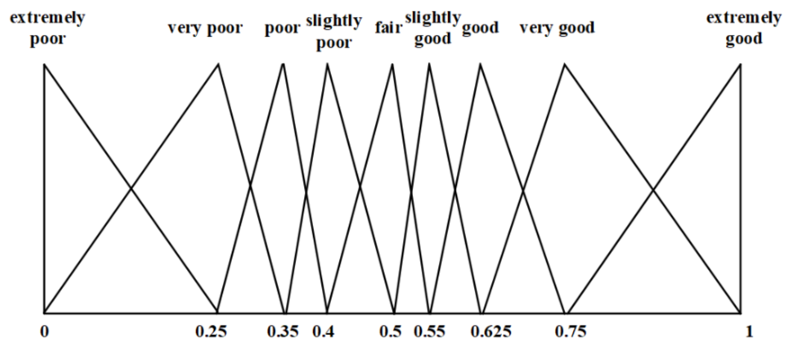


Fig. 5. Fuzzy triangular membership functions.

Definition 8. A triangular fuzzy membership function $A = T(a,b,c)$ is utilized to represent the aggregated outcome of linguistic terms on UHFLTS H_S. Since $s_i = \min H_S, s_j = \max H_S$, the left limit($a$) and right limit($c$) of A can be obtained from s_i and s_j. by Eqs. (11) and (12).

$$a = \min\left\{a_L^i, a_M^i, a_M^{i+1}, \ldots, a_M^j, a_R^j\right\} = a_L^i, \tag{11}$$

$$c = \max\left\{a_L^i, a_M^i, a_M^{i+1}, \ldots, a_M^j, a_R^j\right\} = a_R^j. \tag{12}$$

The residual elements $(a_M^i, a_M^{i+1}, \ldots, a_M^j)$ are aggregated to generate the parameter b of A by MSM operator [53] as Eq. (13).

$$b = MSM^{(k)}(a_M^i, a_M^{i+1}, \ldots, a_M^j) = \left(\frac{\sum_{\substack{i \le m_1 < \\ \ldots < m_k \le j}} \prod_{t=1}^{k} a_M^{m_t}}{C_{j-i+1}^k}\right)^{\frac{1}{k}}. \tag{13}$$

Step 4. Derive the optimal weights of all criteria.

To derive the optimal weights of all criteria, the maximum absolute gaps $\left|\frac{w_B^l}{w_j^l} - env(h_{B_j^l})\right|$ and $\left|\frac{w_j^l}{w_W^l} - env(h_{W_j^l})\right|$ for all j should be minimized [51]. Thus, the constrained optimization model can be constructed as follows:

$$\begin{aligned} &\min \max_j \left\{\left|\frac{w_B^l}{w_j^l} - env(h_{B_j^l})\right|, \left|\frac{w_j^l}{w_W^l} - env(h_{W_j^l})\right|\right\} \\ &s.t. \begin{cases} \sum_j w_j^l = 1 \\ w_j^l \ge 0, \ \ for\ all\ j. \end{cases} \end{aligned} \tag{14}$$

It is noted that $env(h_{B_j^l})$ and $env(h_{W_j^l})$ are triangular fuzzy numbers, which not comply with the classical BWM. In this regard, we adopt the idea provided by Guo and Zhao [42] to solve the optimization model containing triangular fuzzy numbers.

We use the graded mean integration representation (GMIR) to convert the TFNs into crisp numbers.

Definition 9 *([54])*. Let the graded mean integration representation (GMIR) $R(\tilde{a})$ of a TFN $\tilde{a}$ indicate the ranking of triangular fuzzy number.

Let $\tilde{a}=(l,m,u)$, and the GMIR $R(\tilde{a})$ of TFN $\tilde{a}$ can be calculated by

$$R(\tilde{a})=\frac{l+4m+u}{6}. \tag{15}$$

Considering $\xi=(l^{\xi},m^{\xi},u^{\xi}),(l^{\xi}\le m^{\xi}\le u^{\xi})$ as auxiliary variable, and we suppose $\xi^{*}=(\delta^{*},\delta^{*},\delta^{*})$, $\delta^{*}\le l^{\xi}$.Thus, for $\forall l(l=1,2,...,q)$, the relative model in Eq. (14) can be transferred into the following nonlinearly constrained optimization model:

$$\begin{aligned}
&\min\ \xi^{*}\\
&s.t.\begin{cases}
\left|\dfrac{(l_B^w,m_B^w,u_B^w)}{(l_j^w,m_j^w,u_j^w)}-(l_{B_j},m_{B_j},u_{B_j})\right|\le(\delta^{*},\delta^{*},\delta^{*}),\\
\left|\dfrac{(l_j^w,m_j^w,u_j^w)}{(l_W^w,m_W^w,u_W^w)}-(l_{W_j},m_{W_j},u_{W_j})\right|\le(\delta^{*},\delta^{*},\delta^{*}),\\
\sum_{j=1}^{n}R(w_j)=1,\\
l_j^w\le m_j^w\le u_j^w,\\
l_j^w\ge 0,\ for\ all\ j.
\end{cases}
\end{aligned} \tag{16}$$

By solving the series of models as Eq. (16) for $\forall l(l=1,2,...,q)$, the optimal value of ξ^{l} as ξ^{l*} and the optimal fuzzy weights $(w_1^{l*},w_2^{l*},...,w_n^{l*})^T$ $(l=1,2,...,q)$ can be derived.

Step 5. Test the comparison consistency.

In practice, there may be inconsistent for criterion C_j in relation to pairwise comparison. The consistency ratio (CR) is adopted to test whether a fuzzy pairwise comparison is consistent. It is expected that the perfectly multiplicative consistency relation $a_{Bj}\times a_{jw}=a_{BW}$ would occur. Whereas, the inconsistency problem would be more normal. In such situation, we introduce a slack variable γ to adjust the deviation between the perfectly multiplicative preference and the actual preference degree. Thus, we have

$$(a_{Bj}-\gamma)\times(a_{jw}-\gamma)=(a_{BW}+\gamma). \tag{17}$$

It is clear that the greatest inequality occurs when a_{Bj} and a_{jw} have the maximum value, $a_{Bj}=a_{jw}=a_{BW}$, and we have

$$(a_{BW}-\gamma)\times(a_{BW}-\gamma)=(a_{BW}+\gamma)$$
$$\Rightarrow \gamma^2-(1+2a_{BW})\gamma+(a_{BW}{}^2-a_{BW})=0. \tag{18}$$

Through solving for different values of a_{BW}, we can find the maximum possible γ (max γ), which can be deemed as consistency index (CI) of criteria under different pairwise comparisons.

The consistency ratio (CR) can be calculated using ξ^{l*} and the corresponding consistency index as follows:

$$Consistency\ Ratio=\frac{\xi^{l*}}{Consistency\ Index}. \tag{19}$$

It is apparent that the smaller the CR is, the higher consistency will be ensured. Usually, CR<0.1 is acceptable.

If the CR is acceptable, the subjective weight vector of criteria is output as $(w^l_{1(sub)}, w^l_{2(sub)},\ldots, w^l_{n(sub)})^T$ $(l=1,2,\ldots,q)$.

4.3. Stage III-Determine the objective criterion weights based on the maximizing deviation method

Let $S^{(B)}=\left\{s_0^B, s_1^B,\ldots,s_{g-1}^B\right\}$ be the balanced linguistic term set with the cardinality of g, and $S^{(l)}=\left\{s_0^l, s_1^l,\ldots,s_{g(l)-1}^l\right\}$ be the unbalanced linguistic term set with a cardinality $g(l)$ provided by expert e_l. Let $NS^{(l)}$ be the numerical value of $S^{(l)}$, $\underline{NS^{(l)}}=NS^{(l)}(s_0^l)$ and $\overline{NS^{(l)}}=NS^{(l)}(s_{g(l)-1}^l)$. Prior to measuring the objective criterion weights, we adopt the approach proposed by Zhang et al. [41] to transform the UHFLTS $H^{S^{(l)}}=\left\{s_\tau^l, s_{\tau+1}^l,\ldots,s_\sigma^l\right\}$ defined on $S^{(l)}$ provided by expert e_l to corresponding balanced LDA defined on $S^{(B)}$. The conversion procedure comprises three steps as follows:

Step 1. Convert $NS^{(l)}(s_h^l)$ ($s_h^l\in H^{S^{(l)}}, h=\tau,\tau+1,\ldots,\sigma$) to the corresponding numerical scale $NS^{(B)}(s_h^l)$ with the normal support $[0, g-1]$ by Eq. (20).

$$NS^{(B)}(s_h^l)=\frac{g\left(NS^{(l)}(s_h^l)-\underline{NS^{(l)}}\right)}{\overline{NS^{(l)}}-\underline{NS^{(l)}}}. \tag{20}$$

Step 2. Transform $s_h^l\in S^{(l)}$ into the corresponding LDA m_h^l defined on $S^{(B)}$ by Eq. (21).

$$m_h^l = \left\{ \left\langle s_{t_h}^B, 1-\beta_h^B \right\rangle, \left\langle s_{t_h+1}^B, \beta_h^B \right\rangle \right\}, \tag{21}$$

where $t_h = trunc\left(\dfrac{g\left(NS^{(l)}(s_h^l) - \underline{NS^{(l)}} \right)}{\overline{NS^{(l)}} - \underline{NS^{(l)}}} \right)$ and $\beta_h^B = NS^{(B)}(s_h^l) - t_h$, $h = \tau, \tau+1, \ldots, \sigma$.

The $trunc(\cdot)$ function means to remove the fractional part of the number.

Step 3. Aggregate the LDAs into a novel LDA of the balanced linguistic term set $S^{(B)}$ by means of LDAWA operator considering differential importance of m_h .by Eq. (22).

$$m^l = LDAWA_w(m_\tau^l, m_{\tau+1}^l, \ldots, m_\sigma^l), \tag{22}$$

where $m_h^l = \left\{ \left\langle s_{t_h}^B, 1-\beta_h^B \right\rangle, \left\langle s_{t_h+1}^B, \beta_h^B \right\rangle \right\}$ is obtained by Eq. (21), and $w = (1/(\sigma-\tau+1), 1/(\sigma-\tau+1), \ldots, 1/(\sigma-\tau+1))^T$.

According to the previous method, we can convert multi-granular UHFLTSs into balanced LDAs. Hereafter, each x_{ij}^l can be easily converted into an LDA $r_{ij}^l = \{< s_t^B, \beta_{ij,t}^l > | t = 0,1,\ldots, g-1\}$, $0 \le \beta_{ij,t}^l \le 1$ and $\sum_{t=0}^{g-1} \beta_{ij,t}^l = 1$. Thus, each initial UHFLTSs evaluation matrix $X_{g(l)}^l = (x_{ij}^l)_{m\times n}$ can be transformed into the corresponding balanced LDA decision matrix shown as follows:

$$R^l = (r_{ij}^l)_{m\times n} = \begin{array}{c} \\ A_1 \\ A_2 \\ \vdots \\ A_m \end{array} \begin{array}{c} \begin{array}{ccc} C_1 & C_2 & \cdots C_n \end{array} \\ \begin{bmatrix} r_{11}^l & r_{12}^l & \cdots r_{1n}^l \\ r_{21}^l & r_{22}^l & \cdots r_{2n}^l \\ \vdots & \vdots & \ddots \ \vdots \\ r_{m1}^l & r_{m2}^l & \cdots r_{mn}^l \end{bmatrix} \end{array}, l = 1,2,\ldots,q. \tag{23}$$

Subsequently, based on above individual balanced LDA decision matrix R^l , the deviation between any two alternatives with respect to the given criterion C_j^l can be calculated as follows:

$$Dev(C_j^l) = \frac{1}{m(m-1)} \sum_{i_1=1}^{m} \sum_{i_2=1, i_2\neq i_1}^{m} d(r_{i_1 j}^l, r_{i_2 j}^l) = \frac{1}{m(m-1)} \sum_{i_1=1}^{m} \sum_{i_2=1, i_2\neq i_1}^{m} \sqrt{\sum_{t=0}^{g-1} (\beta_{i_1 j,t}^l \times N(s_t) - \beta_{i_2 j,t}^l \times N(s_t))^2}, j = 1,2,\ldots,n, l = 1,2,\ldots,q. \tag{24}$$

To derive the suitable objective weights of criteria, the following model can be constructed:

$$\max \sum_{j=1}^{n} \overline{w}_{(j)obj}^l Dev(C_j^l) = \sum_{j=1}^{n} \overline{w}_{(j)obj}^l \frac{1}{m(m-1)} \sum_{i_1=1}^{m} \sum_{i_2=1, i_2\neq i_1}^{m} \sqrt{\sum_{t=0}^{g-1} (\beta_{i_1 j,t}^l \times N(s_t) - \beta_{i_2 j,t}^l \times N(s_t))} \tag{25}$$

$$s.t.\begin{cases}\sum_{j=1}^{n}(\bar{w}_{(j)obj}^{l})^2=1, & l=1,2,\ldots,q\\ 0\le \bar{w}_{(j)obj}^{l}, & j=1,2,\ldots,n, l=1,2,\ldots,q\end{cases}.$$

To obtain the optimal objective weights of criteria, we construct the Lagrange function as follows:

$$L(\bar{w}_{(j)obj}^{l},\xi)=\sum_{j=1}^{n}\bar{w}_{(j)obj}^{l}\frac{1}{m(m-1)}\sum_{i_1=1}^{m}\sum_{i_2=1,i_2\neq i_1}^{m}\sqrt{\sum_{t=0}^{g-1}(\beta_{i_1j,t}^{l}\times N(s_t)-\beta_{i_2j,t}^{l}\times N(s_t))}+\frac{1}{2}\xi\left(\sum_{j=1}^{n}(\bar{w}_{(j)obj}^{l})^2-1\right) \quad (26)$$

where ξ is the Lagrange multiplier.

Differentiating Eq. (26) with respect to $\bar{w}_{(j)obj}^{l}$ and ξ, respectively, and setting these partial derivatives equal to zero, the following set of equations can be obtained:

$$\begin{cases}\frac{\partial L(\bar{w}_{(j)obj}^{l},\xi)}{\partial \bar{w}_{(j)obj}^{l}}=\frac{1}{m(m-1)}\sum_{i_1=1}^{m}\sum_{i_2=1,i_2\neq i_1}^{m}\sqrt{\sum_{t=0}^{g-1}(\beta_{i_1j,t}^{l}\times N(s_t)-\beta_{i_2j,t}^{l}\times N(s_t))}+\xi\bar{w}_{(j)obj}^{l}=0, & l=1,2,\ldots,q\\ \frac{\partial L(\bar{w}_{(j)obj}^{l},\xi)}{\partial\xi}=\sum_{j=1}^{n}(\bar{w}_{(j)obj}^{l})^2-1=0, l=1,2,\ldots,q. & \end{cases} \quad (27)$$

Solving Eq. (27), we can obtain the objective weight of criterion c_j with respect to expert e_l:

$$\bar{w}_{(j)obj}^{l}=\frac{\frac{1}{m(m-1)}\sum_{i_1=1}^{m}\sum_{i_2=1,i_2\neq i_1}^{m}\sqrt{\sum_{t=0}^{g-1}(\beta_{i_1j,t}^{l}\times N(s_t)-\beta_{i_2j,t}^{l}\times N(s_t))}}{\sqrt{\sum_{l=1}^{q}\left(\frac{1}{m(m-1)}\sum_{i_1=1}^{m}\sum_{i_2=1,i_2\neq i_1}^{m}\sqrt{\sum_{t=0}^{g-1}(\beta_{i_1j,t}^{l}\times N(s_t)-\beta_{i_2j,t}^{l}\times N(s_t))}\right)^2}}, j=1,2,\ldots,n, l=1,2,\ldots,q. \quad (28)$$

Then we further normalize the objective criterion weight to obtain the standard criteria weight as follows:

$$w_{(j)obj}^{l}=\frac{\bar{w}_{(j)obj}^{l}}{\sum_{j=1}^{n}\bar{w}_{(j)obj}^{l}}, l=1,2,\ldots,q. \quad (29)$$

To determine the hybrid criterion weights, we measure the expert's degree of expertise by calculating the distance between his or her subjective and objective criterion weights. The parameter δ_j^l is introduced to represent the reliable degree of expert e_l regarding criterion c_j:

$$\delta_j^l=1-\left|w_{(j)sub}^{l}-w_{(j)obj}^{l}\right|, j=1,2,\ldots,n, l=1,2,\ldots,q. \quad (30)$$

The hybrid criterion weights obtained from e_l is derived by

$$w_j^l=\frac{\delta_j^l\cdot\left(w_{(j)sub}^{l}+w_{(j)obj}^{l}\right)}{\sum_{j=1}^{n}\delta_j^l\cdot\left(w_{(j)sub}^{l}+w_{(j)obj}^{l}\right)}, j=1,2,\ldots,n, l=1,2,\ldots,q. \quad (31)$$

4.4. Stage IV—Energy storage technology selection with unknown expert weight

Let $\lambda_l (l = 1, 2, ..., q)$ be the weight of expert e_l, which is unknown in our method. In the following, we will construct an optimization model based on the ideal of double parameters TOPSIS to derive the weights of experts and further utilize the relative closeness degree to prioritize the alternative ESTs. The procedure consists of the following parts:

Step 1. Obtain the collective LDA matrix R^C by the LDAWA operator as follows:

$$r_{ij} = LDAWA(r_{ij}^1, r_{ij}^2, ..., r_{ij}^q) = \{< s_t, \beta_{ij,t} > | t = 0, 1, ..., g-1\}, \tag{32}$$

where $\beta_{ij,t} = \sum_{l=1}^{q} \lambda_l \beta_{ij,t}^l, t = 0, 1, \ldots, g-1$.

Step 2. Define the linguistic distribution positive ideal solution (LDPIS) and the linguistic distribution negative ideal solution (LDNIS) as

$$r^+ = (r_1^+, r_2^+, ..., r_n^+), \tag{33}$$

$$r^- = (r_1^-, r_2^-, ..., r_n^-), \tag{34}$$

where $r_j^+ = \{< s_t, \beta_{j,t}^+ > | t = 0, 1, \ldots, g-1\}$, the components of the vector $\beta_j^+ = (\beta_{j,0}^+, \beta_{j,1}^+, ..., \beta_{j,g-1}^+)$ can be determined based on Eq. (6) as follows:

$$\beta_j^+ = \begin{cases} \beta_{j,0}^+ = 0 \\ \beta_{j,1}^+ = 0 \\ \quad \vdots \\ \beta_{j,k-1}^+ = 0 \\ \beta_{j,k}^+ = 1 - \sum_{v=k+1}^{g-1} \beta_{j,v}^+ \\ \beta_{j,k+1}^+ = \max_{1 \le l \le q}\{\max_{1 \le i \le m}\{\beta_{ij,k+1}^l\}\} \\ \quad \vdots \\ \beta_{j,g-2}^+ = \max_{1 \le l \le q}\{\max_{1 \le i \le m}\{\beta_{ij,g-2}^l\}\} \\ \beta_{j,g-1}^+ = \max_{1 \le l \le q}\{\max_{1 \le i \le m}\{\beta_{ij,g-1}^l\}\} \end{cases} \tag{35}$$

and $r_j^- = \{< s_t, \beta_{j,t}^- > | t = 0, 1, \ldots, g-1\}$, the components of the vector $\beta_j^- = (\beta_{j,0}^-, \beta_{j,1}^-, ..., \beta_{j,g-1}^-)$ can be determined based on Eq. (8) as follows:

$$\beta_j^- = \begin{cases} \beta_{j,0}^- = \max_{1\le l\le q}\{\max_{1\le i\le m}\{\beta_{ij,0}^l\} \\ \beta_{j,1}^- = \max_{1\le l\le q}\{\max_{1\le i\le m}\{\beta_{ij,1}^l\} \\ \vdots \\ \beta_{j,\varepsilon-1}^- = \max_{1\le l\le q}\{\max_{1\le i\le m}\{\beta_{ij,\varepsilon-1}^l\} \\ \beta_{j,\varepsilon}^- = 1-\sum_{v=0}^{\varepsilon-1}\beta_{v,j}^- \\ \beta_{j,\varepsilon+1} = 0 \\ \vdots \\ \beta_{j,g-2}^- = 0 \\ \beta_{j,g-1}^- = 0 \end{cases} . \tag{36}$$

Step 3. Calculate the distances of each alternative towards the LDPIS and LDNIS, respectively.

$$d_i^+ = \sum_{j=1}^m w_j d(r_{ij}, r_j^+) = \sum_{j=1}^m \left(\sum_{l=1}^q w_j^l \lambda_l \right) \times \sqrt{\sum_{t=0}^{g-1} \left[\sum_{l=1}^q \lambda_l \beta_{ij,t}^l \times N(s_t) - \beta_{j,t}^+ \times N(s_t) \right]^2}, \tag{37}$$

$$d_i^- = \sum_{j=1}^m w_j d(r_{ij}, r_j^-) = \sum_{j=1}^m \left(\sum_{l=1}^q w_j^l \lambda_l \right) \times \sqrt{\sum_{t=0}^{g-1} \left[\sum_{l=1}^q \lambda_l \beta_{ij,t}^l \times N(s_t) - \beta_{j,t}^- \times N(s_t) \right]^2}. \tag{38}$$

The basic principle of double parameters TOPSIS method is that the optimal alternative A_i is the one farthest from the negative ideal solution and closest to the positive ideal solution, namely, the larger d_i^- and smaller d_i^+. Thus, the relative closeness degree $\theta(A_i)$ of alternative A_i can be calculated as follow:

Step 4. Establish the relative closeness degree $\theta(A_i)$ with double parameters corresponding to the ideal solution of $A_i (i = 1, 2, ..., n)$.

$$\theta(A_i) = \frac{(\tau d_i^-)^{2-\kappa}}{(2-\kappa)\tau d_i^+ + \kappa(1-\tau)d_i^-}, \tag{39}$$

where τ $(0 < \tau < 1)$ is called the risk appetite of experts, κ $(0 \le \kappa \le 2)$ is termed as the optimism coefficient to decision preference [18]. The criteria of setting optimism coefficient are listed in Table 3.

Step 5. Construct an optimization model M-1 with double parameters to derive the weight of experts.

$$\max\theta(A_i)=\max\frac{(\tau d_i^-)^{2-\kappa}}{(2-\kappa)\tau d_i^+ +\kappa(1-\tau)d_i^-}$$

$$=\max\frac{\left(\tau\sum_{j=1}^{m}\left(\sum_{l=1}^{q}w_j^l\lambda_l\right)\times\sqrt{\sum_{t=0}^{g-1}\left[\sum_{l=1}^{q}\lambda_l\beta_{ij,t}^l\times N(s_t)-\beta_{j,t}^-\times N(s_t)\right]^2}\right)^{2-\kappa}}{(2-\kappa)\tau\sum_{j=1}^{m}\left(\sum_{l=1}^{q}w_j^l\lambda_l\right)\times\sqrt{\sum_{t=0}^{g-1}\left[\sum_{l=1}^{q}\lambda_l\beta_{ij,t}^l\times N(s_t)-\beta_{j,t}^+\times N(s_t)\right]^2}+\kappa(1-\tau)\sum_{j=1}^{m}\left(\sum_{l=1}^{q}w_j^l\lambda_l\right)\times\sqrt{\sum_{t=0}^{g-1}\left[\sum_{l=1}^{q}\lambda_l\beta_{ij,t}^l\times N(s_t)-\beta_{j,t}^-\times N(s_t)\right]^2}}$$

$$s.t.\begin{cases}\lambda_l\geq 0, l=1,2,...,q,\\ \sum_{l=1}^{q}\lambda_l=1.\end{cases}\tag{40}$$

Since each alternative is non-inferior, we aggregate the above optimization model of each alternative with equal weights into the following collective optimization model M-2:

$$\max\sum_{i=1}^{n}\theta(A_i)=\max\sum_{i=1}^{n}\frac{(\tau d_i^-)^{2-\kappa}}{(2-\kappa)\tau d_i^+ +\kappa(1-\tau)d_i^-}$$

$$=\max\sum_{i=1}^{n}\left(\frac{\left(\tau\sum_{j=1}^{m}\left(\sum_{l=1}^{q}w_j^l\lambda_l\right)\times\sqrt{\sum_{t=0}^{g-1}\left[\sum_{l=1}^{q}\lambda_l\beta_{ij,t}^l\times N(s_t)-\beta_{j,t}^-\times N(s_t)\right]^2}\right)^{2-\kappa}}{(2-\kappa)\tau\sum_{j=1}^{m}\left(\sum_{l=1}^{q}w_j^l\lambda_l\right)\times\sqrt{\sum_{t=0}^{g-1}\left[\sum_{l=1}^{q}\lambda_l\beta_{ij,t}^l\times N(s_t)-\beta_{j,t}^+\times N(s_t)\right]^2}+\kappa(1-\tau)\sum_{j=1}^{m}\left(\sum_{l=1}^{q}w_j^l\lambda_l\right)\times\sqrt{\sum_{t=0}^{g-1}\left[\sum_{l=1}^{q}\lambda_l\beta_{ij,t}^l\times N(s_t)-\beta_{j,t}^-\times N(s_t)\right]^2}}\right)$$

$$s.t.\begin{cases}\lambda_l\geq 0, l=1,2,...,q,\\ \sum_{l=1}^{q}\lambda_l=1.\end{cases}\tag{41}$$

Based on the particular value of risk appetite τ and optimism coefficient κ, the optimal weight $\lambda^*=(\lambda_1^*,\lambda_2^*,...,\lambda_q^*)$ can be derived by solving the model M-2. Then we can obtain the value of $\theta(A_i)$ ($i=1,2,...,m$).

Step 6. Rank all ESTs in descending order in accordance with $\theta(A_i)$ $(i=1,2,...,n)$. For available ESTs, the bigger the relative closeness degree is, the better performance of the EST is. That is to say, the EST with the biggest relative closeness degree should be given the highest priority.

Table 3

Criteria for setting optimism coefficient.

Decision-maker judgement	Optimism coefficient (κ)
Maximum optimism-decision	2
Tend to pursue optimism-decision	(1,2)
Neutral-decision	1
Tend to pursue pessimistic-decision	(0,1)
Minimum pessimistic-decision	0

5. Case study

In order to response to the structural adjustment in primary energy, China has accelerated the development of wind power and made sustainable process. From 2010-2020, the installed capacity of wind power in China has been growing steadily as shown in Fig. 6. As a major province of wind power generation with a total power of 672.8 MW at the end of 2020, Inner Mongolia has still been facing a severe wind curtailment rate problem. The primary reason is that there are insufficient industries and advanced technologies for consuming wind power. For a renewable energy storage project under construction in Inner Mongolia, it intends to select a desirable EST for storing wind resources on wind farm. After preliminary investigation, seven feasible ESTs reserve for further evaluation: flow batteries energy storage (Flow BES) (A_1), flywheel energy storage (FES) (A_2), compressed air energy storage (CAES) (A_3), Li-ion battery energy storage (Li-ion BES) (A_4), superconducting magnetic energy storage (SMES) (A_5), supercapacitors (SCES) (A_6), pumped hydro energy storage (PHES) (A_7). Assume that a decision committee composed of three experts e_1, e_2, e_3 from different domains is formed to evaluate ESTs according to the index system. Some data related to technical and economic index for the alternative ESTs are collected as shown in Table 4, which can serve as a reference for the assessment of EST by experts. Due to the vagueness and imprecise knowledge of experts, they utilize multi-granular UHFLTSs to elicit their assessments. The semantics and numerical values of the unbalanced linguistic term sets used by the three experts are listed in Tables A.1-A.3 in Appendix, respectively.

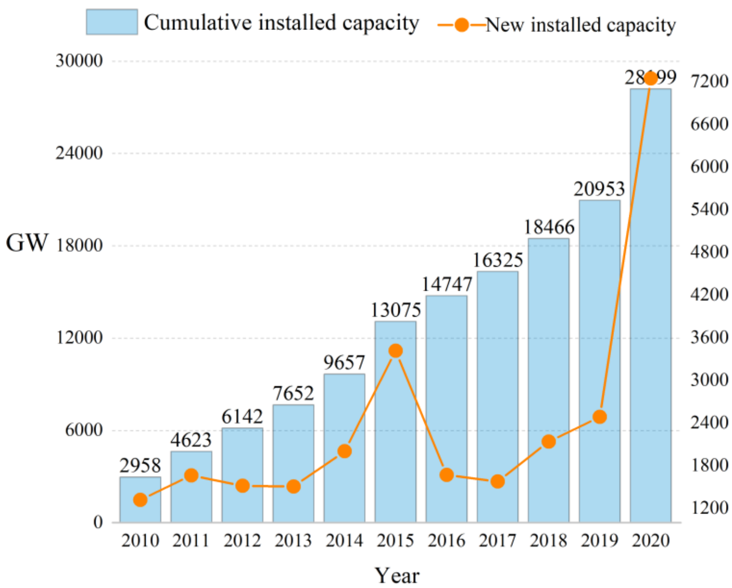


Fig. 6. Cumulative wind power installed and new installed capacities in China from 2010~2020.

Table 4

Different characteristics parameters of ESTs in technical and economic perspectives.

EST	Cost		Storage Capacity (MW)	Energy density (Wh/kg)	Power transmission rate (%)	Lifetime (Cycles)	Response delay time	Maturity
	Capital Cost($/kw)	O&M ($/MWh)						
Flow BES	700-2520	0.24-8.48	0.03-3	20-70	65-85	2000-10000	<100ms	Commercial
FES	294-2880	0.77-5.06	0-15	20-80	93-95	20,000-100,000	~s	Demonstration
CAES	400-800	2.39-3.88	5-400	2-6	40-70	8000-12,000	9-12min	Commercial
Li-ion BES	1200-4000	0.7-8.07	0-100	250-750	90-95	2000-10,000	~ms	Demonstration
SMES	140-636	—	0.1-10	0.2-2.5	95-98	>10,000	~ms	Developed
SCES	140-560	—	0-0.3	10-30	90-95	100,000-1,000,000	~ms	Developed
PHES	1700-5100	0.47-2.14	100-5000	0.5-1.5	75-85	20,000-50,000	mins	Mature

Source: Wu et al. [36]; Elio et al. [55]; Daim et al. [20]; Ren and ren [31].

5.1. Solving the case by the proposed multistage framework

Stage 1: collect the evaluation information

The initial multi-granular UHFLTSs decision matrices $X^{l}_{g(l)} = (x^{l}_{ij})_{7\times 12} (k = 1, 2, 3)$ are constructed as shown in Table A.7.

Stage II: determine the subjective criterion weight vector

Table 5

The best and worst criteria determined by experts.

	e_1	e_2	e_3
C_B	C_3	C_5	C_4
C_W	C_{10}	C_{12}	C_{12}

Steps 1-3. After determining the best and the worst criteria in Table 5, experts provide corresponding preference vectors with multi-granular UHFLTSs based on the linguistic variables listed in Tables A.4-A.6, which are further converted into BO and OW vectors defined on unbalanced linguistic term set $S^{(l)}$.

$$BO = \begin{array}{c} (C_B) \\ e_1(C_3) \\ e_2(C_5) \\ e_3(C_4) \\ \\ e_1(C_3) \\ e_2(C_5) \\ e_3(C_4) \end{array} \begin{bmatrix} C_1 & C_2 & C_3 & C_4 & C_5 & C_6 \\ \{s_2^1, s_3^1\} & \{s_3^1, s_4^1\} & \{s_0^1\} & \{s_0^1, s_1^1\} & \{s_1^1, s_2^1\} & \{s_2^1\} \\ \{s_4^2, s_5^2\} & \{s_5^2, s_6^2\} & \{s_0^2, s_1^2, s_2^2\} & \{s_2^2\} & \{s_0^2\} & \{s_2^2, s_3^2, s_4^2\} \\ \{s_5^3, s_6^3\} & \{s_3^3, s_4^3\} & \{s_1^3\} & \{s_0^3\} & \{s_0^3, s_1^3, s_2^3\} & \{s_2^3\} \\ C_7 & C_8 & C_9 & C_{10} & C_{11} & C_{12} \\ \{s_2^1, s_3^1\} & \{s_3^1, s_4^1\} & \{s_3^1\} & \{s_4^1\} & \{s_1^1, s_2^1, s_3^1\} & \{s_2^1, s_3^1, s_4^1\} \\ \{s_3^2, s_4^2, s_5^2\} & \{s_5^2\} & \{s_5^2, s_6^2\} & \{s_3^2, s_4^2\} & \{s_2^2, s_3^2, s_4^2\} & \{s_6^2\} \\ \{s_2^3, s_3^3\} & \{s_3^3, s_4^3, s_5^3\} & \{s_5^3\} & \{s_5^3, s_6^3\} & \{s_3^3, s_4^3\} & \{s_8^3\} \end{bmatrix}$$

$$OW = \begin{array}{c} (C_W) \\ e_1(C_{10}) \\ e_2(C_{12}) \\ e_3(C_{12}) \\ \\ e_1(C_{10}) \\ e_2(C_{12}) \\ e_3(C_{12}) \end{array} \begin{bmatrix} C_1 & C_2 & C_3 & C_4 & C_5 & C_6 \\ \{s_1^1, s_2^1, s_3^1\} & \{s_0^1, s_1^1\} & \{s_4^1\} & \{s_3^1, s_4^1\} & \{s_2^1, s_3^1\} & \{s_1^1, s_2^1\} \\ \{s_3^2, s_4^2\} & \{s_1^2, s_2^2, s_3^2\} & \{s_5^2, s_6^2\} & \{s_4^2, s_5^2\} & \{s_6^2\} & \{s_4^2, s_5^2\} \\ \{s_2^3, s_3^3\} & \{s_2^3, s_3^3, s_4^3\} & \{s_5^3\} & \{s_8^3\} & \{s_4^3\} & \{s_3^3, s_4^3\} \\ C_7 & C_8 & C_9 & C_{10} & C_{11} & C_{12} \\ \{s_2^1\} & \{s_1^1, s_2^1\} & \{s_0^1, s_1^1\} & \{s_0^1\} & \{s_2^1\} & \{s_0^1, s_1^1, s_2^1\} \\ \{s_4^2\} & \{s_2^2, s_3^2, s_4^2\} & \{s_1^2, s_2^2\} & \{s_0^2, s_1^2\} & \{s_2^2, s_3^2\} & \{s_0^2\} \\ \{s_5^3\} & \{s_3^3, s_4^3, s_5^3\} & \{s_0^3, s_1^3, s_2^3\} & \{s_0^3, s_1^3\} & \{s_2^3, s_3^3\} & \{s_0^3\} \end{bmatrix}$$

Then the envelop of each element in BO and OW preference vectors can be derived by Eqs. (11)-(13).

$$BO = \begin{array}{c} \\ e_1 \\ e_2 \\ e_3 \\ \\ e_1 \\ e_2 \\ e_3 \end{array} \begin{bmatrix} c_1 & c_2 & c_3 & c_4 & c_5 & c_6 \\ (1, 2.121, 4) & (1.5, 3.464, 5) & (1,1,1) & (1,1,1.5) & (1, 2.121, 3) & (1,1.5,3) \\ (2, 3.162, 5.5) & (2.5, 4.743, 7) & (1,1.155, 2) & (1,1.5, 2) & (1,1,1) & (1,1.979, 4) \\ (4, 5.701, 7) & (2, 3.464, 5) & (1,1, 2) & (1,1,1) & (1,1.29, 3) & (1, 2, 3) \\ c_7 & c_8 & c_9 & c_{10} & c_{11} & c_{12} \\ (1, 2.121, 4) & (1.5, 3.464, 5) & (1.5, 3, 4) & (3, 4, 5) & (1,1.732, 4) & (1, 2.739, 5) \\ (1.5, 2.769, 5) & (2.5, 4.5, 5) & (2.5, 4.743, 7) & (1.5, 2.236, 4) & (1,1.979, 4) & (4.5, 5, 7) \\ (1, 2.45, 4) & (2, 3.958, 6.5) & (4, 5, 6.5) & (4, 5.701, 7) & (2, 3.464, 5) & (7, 8, 9) \end{bmatrix}$$

$$OW = \begin{array}{c} \\ e_1 \\ e_2 \\ e_3 \\ \\ e_1 \\ e_2 \\ e_3 \end{array} \begin{bmatrix} c_1 & c_2 & c_3 & c_4 & c_5 & c_6 \\ (1,1.732, 4) & (1,1,1.5) & (3, 4, 5) & (1.5, 3.464, 5) & (1, 2.121, 4) & (1, 2.121, 3) \\ (1.5, 2.236, 4) & (1,1.472, 2.5) & (2.5, 4.743, 7) & (2, 3.162, 5.5) & (4.5, 5, 7) & (2, 3.162, 5.5) \\ (1, 2.45, 4) & (1, 2.94, 5) & (4, 5, 6.5) & (7, 8, 9) & (3, 4, 5) & (2, 3.464, 5) \\ c_7 & c_8 & c_9 & c_{10} & c_{11} & c_{12} \\ (1,1.5, 3) & (1, 2.121, 3) & (1,1,1.5) & (1,1,1) & (1,1.5, 3) & (1,1.155, 3) \\ (2, 2.5, 4) & (1,1.979, 4) & (1,1.225, 2) & (1,1,1.5) & (1,1.732, 2.5) & (1,1,1) \\ (4, 5, 6.5) & (2, 3.958, 6.5) & (1,1.29, 3) & (1,1, 2) & (1,1.25, 4) & (1,1,1) \end{bmatrix}$$

Step 4. Solving the optimization model based on Eq. (16) by lingo software, we obtain the optimal weights of all criteria $(w_1^{l*}, w_2^{l*}, ..., w_{12}^{l*})$ $(l = 1, 2, 3)$ as presented in Tables 6-8 and optimal values of ξ^{l*}. The results are acceptable for satisfying the comparison consistency:

$CR_1 = \frac{\xi^{1*}}{CI_1} = \frac{0.555}{7.37} = 0.075 < 0.1$, $CR_2 = \frac{\xi^{2*}}{CI_2} = \frac{0.816}{9.35} = 0.087 < 0.1$ and $CR_3 = \frac{\xi^{3*}}{CI_3} = \frac{1.088}{12.53} = 0.080 < 0.1$.

Stage III: derive the objective criterion weight vector

$S^{(B)} = \{s_0^B, s_1^B, \ldots, s_4^B\}$ is settled as the balanced linguistic term set with the cardinality of 5. Hereafter, we apply the method in Section 4.3 to transfer the UHFLTSs decision matrices X_5^1, X_7^2 and X_9^3 into the corresponding balanced LDA decision matrices $R^l = (r_{ij}^l)_{7\times12} (l = 1, 2, 3)$ defined on $S^{(B)}$. Then the total deviation among alternatives with respect to each criterion can be obtained by Eq. (24). Through solving the optimization model in Eq. (25), the objective criterion weights with respect to expert e_l $(l = 1, 2, 3)$ are listed in Tables 6-8. Combining subjective criteria weights obtained in Stage II, the hybrid weight for each expert can be calculated by Eqs. (30) and (31) as shown in Tables 6-8 respectively.

Table 6

Criteria weights with respect to expert e_1.

Criteria(e_1)	Subjective weight	Objective weight	Hybrid weight
C_1	0.085	0.107	0.097
C_2	0.054	0.065	0.061
C_3	0.160	0.102	0.128
C_4	0.144	0.049	0.091
C_5	0.096	0.109	0.105
C_6	0.091	0.062	0.077
C_7	0.074	0.102	0.089
C_8	0.062	0.114	0.086
C_9	0.054	0.063	0.060
C_{10}	0.039	0.061	0.051
C_{11}	0.074	0.104	0.089
C_{12}	0.067	0.062	0.066

Table 7

Criteria weights with respect to expert e_2.

Criteria(e_2)	Subjective weight	Objective weight	Hybrid weight
C_1	0.068	0.085	0.079

C_2	0.044	0.113	0.077
C_3	0.164	0.099	0.129
C_4	0.126	0.086	0.107
C_5	0.155	0.043	0.093
C_6	0.120	0.063	0.091
C_7	0.079	0.095	0.090
C_8	0.048	0.080	0.065
C_9	0.042	0.066	0.055
C_{10}	0.052	0.104	0.078
C_{11}	0.071	0.078	0.077
C_{12}	0.031	0.088	0.059

Table 8

Criteria weights with respect to expert e_3.

Criteria(e_3)	Subjective weight	Objective weight	Hybrid weight
C_1	0.049	0.087	0.068
C_2	0.061	0.071	0.068
C_3	0.109	0.108	0.113
C_4	0.223	0.054	0.120
C_5	0.104	0.095	0.103
C_6	0.091	0.099	0.098
C_7	0.112	0.091	0.104
C_8	0.078	0.064	0.073
C_9	0.051	0.104	0.077
C_{10}	0.044	0.092	0.068
C_{11}	0.053	0.082	0.068
C_{12}	0.025	0.054	0.040

Stage IV: Acquire the unknown expert weight and prioritize ESTs.

According to Eqs. (35) and (36), we can construct LDPIS r^+ and LDNIS r^- as shown in Table 9.

Table 9

Linguistic distribution positive ideal solution (LDPIS) and negative ideal solution (LDNIS).

	LDPIS r^+	LDNIS r^-
r_1	$\{<s_0,0>,<s_1,0>,<s_2,0>,<s_3,0>,<s_4,1>\}$	$\{<s_0,0.333>,<s_1,0.4>,<s_2,0.267>,<s_3,0>,<s_4,0>\}$
r_2	$\{<s_0,0>,<s_1,0>,<s_2,0>,<s_3,0>,<s_4,1>\}$	$\{<s_0,0.333>,<s_1,0.5>,<s_2,0.167>,<s_3,0>,<s_4,0>\}$
r_3	$\{<s_0,0>,<s_1,0>,<s_2,0>,<s_3,0>,<s_4,1>\}$	$\{<s_0,0.333>,<s_1,0.6>,<s_2,0.067>,<s_3,0>,<s_4,0>\}$
r_4	$\{<s_0,0>,<s_1,0>,<s_2,0>,<s_3,0.3>,<s_4,0.7>\}$	$\{<s_0,0>,<s_1,0.233>,<s_2,0.767>,<s_3,0>,<s_4,0>\}$
r_5	$\{<s_0,0>,<s_1,0>,<s_2,0>,<s_3,0>,<s_4,1>\}$	$\{<s_0,0.33>,<s_1,0.33>,<s_2,0.34>,<s_3,0>,<s_4,0>\}$
r_6	$\{<s_0,0>,<s_1,0>,<s_2,0>,<s_3,0.533>,<s_4,0.467>\}$	$\{<s_0,0>,<s_1,0.5>,<s_2,0.5>,<s_3,0>,<s_4,0>\}$
r_7	$\{<s_0,0>,<s_1,0>,<s_2,0>,<s_3,0>,<s_4,1>\}$	$\{<s_0,0.333>,<s_1,0.5>,<s_2,0.167>,<s_3,0>,<s_4,0>\}$

r_8	$\{<s_0,0>,<s_1,0>,<s_2,0>,<s_3,0>,<s_4,1>\}$	$\{<s_0,0.5>,<s_1,0.5>,<s_2,0>,<s_3,0>,<s_4,0>\}$
r_9	$\{<s_0,0>,<s_1,0>,<s_2,0>,<s_3,0.5>,<s_4,0.5>\}$	$\{<s_0,0.333>,<s_1,0.5>,<s_2,0.167>,<s_3,0>,<s_4,0>\}$
r_{10}	$\{<s_0,0>,<s_1,0>,<s_2,0>,<s_3,0.3>,<s_4,0.7>\}$	$\{<s_0,0.333>,<s_1,0.5>,<s_2,0.167>,<s_3,0>,<s_4,0>\}$
r_{11}	$\{<s_0,0>,<s_1,0>,<s_2,0>,<s_3,0>,<s_4,1>\}$	$\{<s_0,0.333>,<s_1,0.5>,<s_2,0.167>,<s_3,0>,<s_4,0>\}$
r_{12}	$\{<s_0,0>,<s_1,0>,<s_2,0>,<s_3,0.3>,<s_4,0.7>\}$	$\{<s_0,0>,<s_1,0.5>,<s_2,0.5>,<s_3,0>,<s_4,0>\}$

The optimization model for deriving the expert weights can be constructed by Eq. (41) as follows (assuming that $\tau=0.6$, $\kappa=0.8$):

$$\min \sum_{i=1}^{7} \theta(A_i)$$

$$= \min \sum_{i=1}^{n} \left(\frac{\left(0.6 \times \sum_{j=1}^{m} \left(\sum_{l=1}^{q} w_j^l \lambda_l \right) \times \sqrt{\sum_{t=0}^{4} \left[\sum_{l=1}^{3} \lambda_l \beta_{ij,t}^l \times N(s_t) - \beta_{j,t}^- \times N(s_t) \right]^2}\right)^{2-0.8}}{(2-0.8) \times 0.6 \times \sum_{i=1}^{7} \sum_{j=1}^{12} \left(\sum_{l=1}^{3} w_j^l \lambda_l \right) \times \sqrt{\sum_{t=0}^{4} \left[\sum_{l=1}^{3} \lambda_l \beta_{ij,t}^l \times N(s_t) - \beta_{j,t}^+ \times N(s_t) \right]^2} + 0.8 \times (1-0.6) \sum_{j=1}^{m} \left(\sum_{l=1}^{q} w_j^l \lambda_l \right) \times \sqrt{\sum_{t=0}^{4} \left[\sum_{l=1}^{3} \lambda_l \beta_{ij,t}^l \times N(s_t) - \beta_{j,t}^- \times N(s_t) \right]^2}} \right)$$

$$s.t. \begin{cases} \lambda_1 \geq 0, \lambda_2 \geq 0, \lambda_3 \geq 0 \\ \lambda_1 + \lambda_2 + \lambda_3 = 1 \end{cases}.$$

By this model, we can obtain the optimal weight of each expert:

$\lambda_1=0.283$, $\lambda_2=0.457$, $\lambda_2=0.260$,

and the distances of each alternative towards the LDPIS and LDNIS:

$$d_1^+ = 3.178, d_2^+ = 3.114, d_3^+ = 3.265, d_4^+ = 3.327, d_5^+ = 2.996, d_6^+ = 3.248, d_7^+ = 2.915;$$
$$d_1^- = 1.382, d_2^- = 1.417, d_3^- = 1.399, d_4^- = 1.389, d_5^- = 1.464, d_6^- = 1.317, d_7^- = 1.461.$$

Furthermore, the relative closeness degree of each alternative ca be obtained by Eq. (39).

$\theta(A_1)=0.293$, $\theta(A_2)=0.305$, $\theta(A_3)=0.290$, $\theta(A_4)=0.283$, $\theta(A_5)=0.326$, $\theta(A_6)=0.273$, $\theta(A_7)=0.333$.

Then, final evaluation result can be determined as $A_6 \prec A_4 \prec A_3 \prec A_1 \prec A_2 \prec A_5 \prec A_7$ in terms of the relative closeness degree.

5.2. Performance analysis

In this section, sensitivity analysis and comparative analysis are conducted to verify the reliability and robustness of the proposed approach.

5.2.1. Sensitivity analysis with criteria weight fluctuations

The final outcomes of MCGDM method depend on the weights of criteria to a large extent. To observe the impact of the fluctuation in criteria weights on the final ranking, the weights are adjusted to $\pm 30\%$ from their base values. Within the ranges of weights, we acquire 100 groups of random combinations of criteria weights through Monte Carlo simulation and the total weight ensures to be equal to 1. Some variations on final ranking of each EST related to different groups of criteria weights can be apparently observed in Fig. 7, which indicates the rankings are sensitive to the criteria weights. Whereas, the ranking results appear to be robust to some extent with no drastic changes appearing. As shown in Fig. 7, A_7 is always the best technology, A_2 and A_5 rank as the second or the third one, A_1 is mostly the forth one, A_3 and A_4 rank as the five or the six one and A_6 ranks as the last one in most cases.

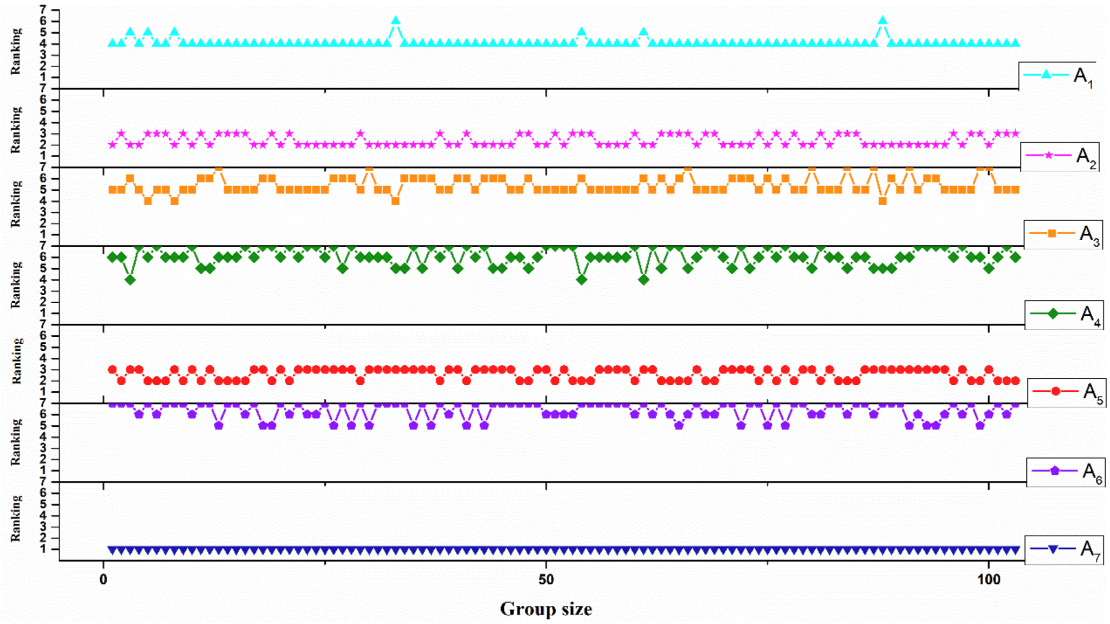


Fig. 7. Ranking results change with $\pm 30\%$ variation of criteria weights.

To further explore the impact of the fluctuation in criteria weights on the final ranking, the ranges of criteria weights are enlarged to the whole interval [0,1], the changes in ranking results of such 7 technologies obtained by 100 simulations are presented in Fig. 8. From Fig. 8, it is apparent that rankings are more sensitive to criteria weights but still have robustness, i.e. A_7 ranks as the best one and A_6 ranks as the least one in most cases and other technologies are in the relative inferiority. Whereas, A_5 and A_2 are obviously, superior to alternatives A_1, A_3, and A_4, which conforms with the tendency of the rankings derived from the criteria weights with $\pm 30\%$ variation. From the above two situations of varying criteria weights, it can be certified that the proposed approach possesses reliability and robustness.

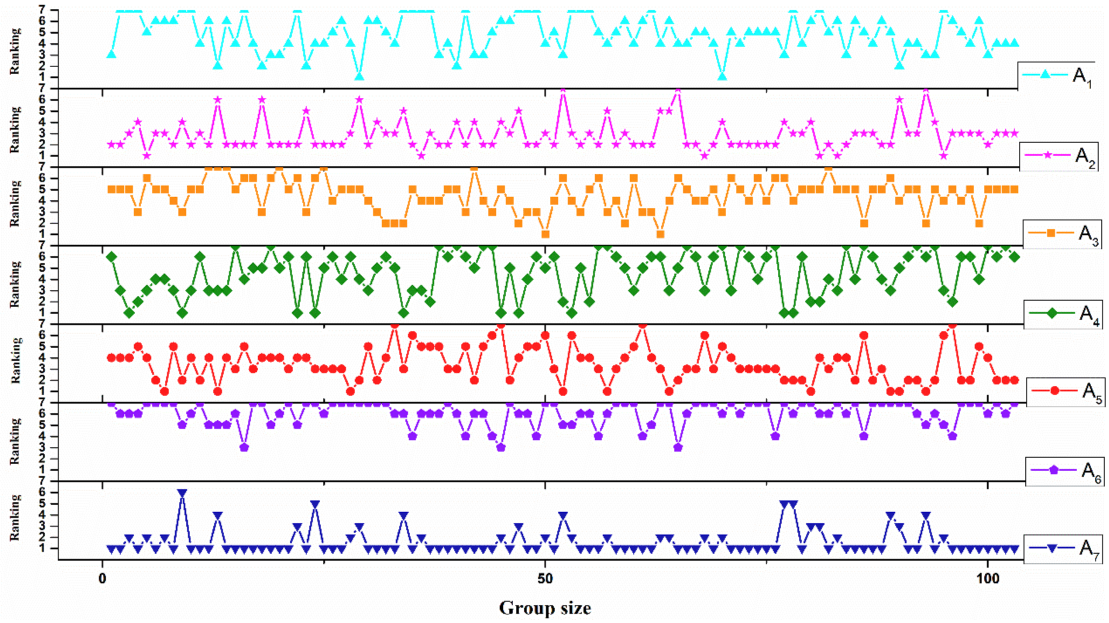
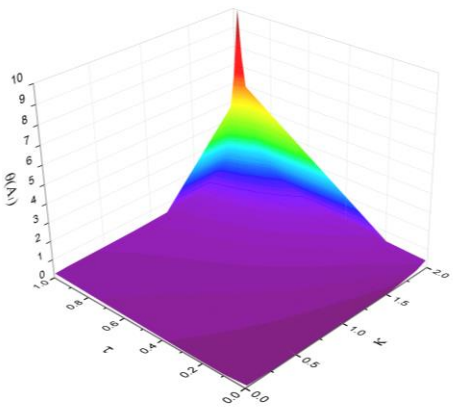


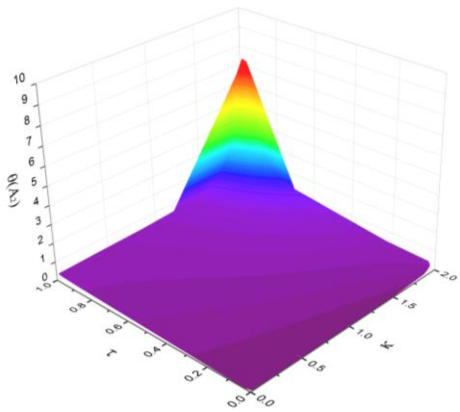
Fig. 8. Ranking results change with criteria weights in interval [0,1].

5.2.2 Sensitivity analysis with double parameters τ *and* κ

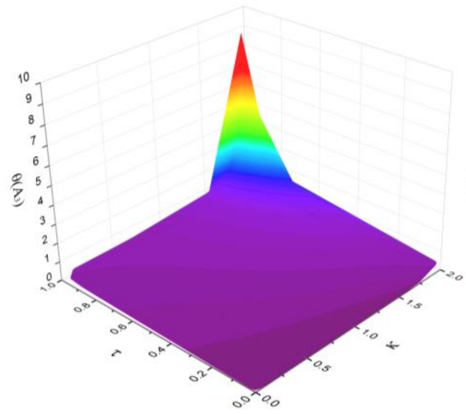
In this subsection, sensitivity analyses are separately conducted with 10000 simulation experiments to reveal the influence of the risk appetite of experts τ and the optimism coefficient κ on the relative closeness degree $\theta(A_i)$. In our experiments, τ varies in interval [0,1] and κ varies in interval [0,2]. From Fig. 9, the following observations can be distinguished, the values of $\theta(A_i)(i=1,2,...,7)$ are gradually increasing with the increase of optimism coefficient κ when the risk appetite of experts τ is fixed. Meanwhile, the values of $\theta(A_i)(i=1,2,...,7)$ are gradually increasing with the increase of the risk appetite of experts τ when the optimism coefficient κ is fixed.

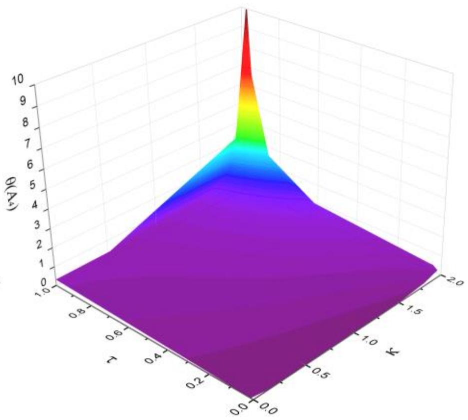


(a)

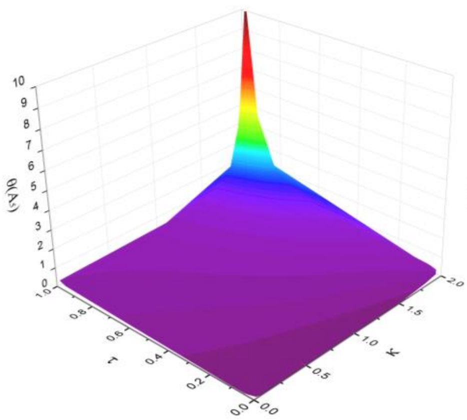


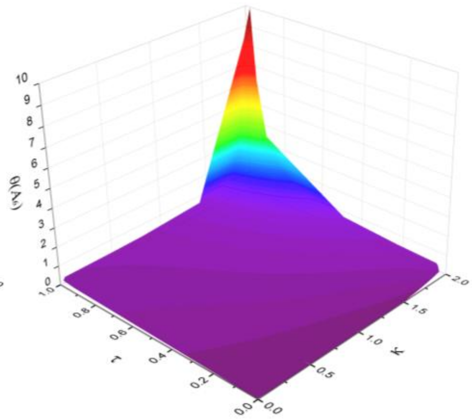
(b)



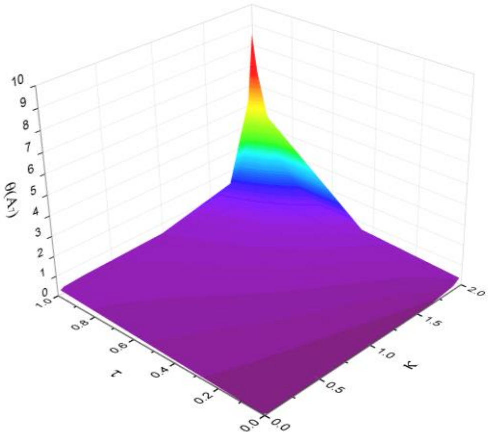


(c) (d)





(e) (f)



(g)

Fig. 9. The influence of τ and κ to the relative closeness degree $\theta(A_i)$

Table 10

Ranking results.

Optimism coefficient κ risk appetite of experts τ	The value of $\theta(A_i)$	Ranking order	Optimal alternative
$\tau=\frac{1}{4},\kappa=1$	(0.183,0.198,0.189,0.192,0.187,0.185,0.200)	$A_6 \prec A_4 \prec A_3 \prec A_1 \prec A_2 \prec A_5 \prec A_7$	A_7
$\tau=\frac{1}{2},\kappa=1$	(0.288,0.328,0.303,0.313,0.300,0.295,0.334)	$A_1 \prec A_6 \prec A_5 \prec A_3 \prec A_4 \prec A_2 \prec A_7$	A_7
$\tau=\frac{3}{4},\kappa=1$	(0.357,0.420,0.380,0.395,0.375,0.366,0.429)	$A_1 \prec A_6 \prec A_5 \prec A_3 \prec A_4 \prec A_2 \prec A_7$	A_7
$\tau=\frac{1}{4},\kappa=\frac{1}{2}$	(0.110,0.132,0.119,0.124,0.118,0.116,0.135)	$A_1 \prec A_6 \prec A_5 \prec A_3 \prec A_4 \prec A_2 \prec A_7$	A_7
$\tau=\frac{3}{4},\kappa=\frac{1}{2}$	(0.257,0.324,0.282,0.298,0.279,0.271,0.331)	$A_1 \prec A_6 \prec A_5 \prec A_3 \prec A_4 \prec A_2 \prec A_7$	A_7
$\tau=\frac{1}{4},\kappa=\frac{3}{2}$	(0.304,0.299,0.301,0.300,0.298,0.297,0.301)	$A_6 \prec A_5 \prec A_2 \prec A_4 \prec A_3 = A_7 \prec A_1$	A_1
$\tau=\frac{3}{4},\kappa=\frac{3}{2}$	(0.581,0.627,0.595,0.607,0.586,0.577,0.638)	$A_6 \prec A_1 \prec A_5 \prec A_3 \prec A_4 \prec A_2 \prec A_7$	A_7
$\tau=\frac{1}{4},\kappa=2$	(0.506,0.455,0.482,0.470,0.477,0.480,0.456)	$A_2 \prec A_7 \prec A_4 \prec A_5 \prec A_6 \prec A_3 \prec A_1$	A_1
$\tau=\frac{1}{2},\kappa=2$	(0.759,0.683,0.724,0.706,0.715,0.720,0.684)	$A_2 \prec A_7 \prec A_4 \prec A_5 \prec A_6 \prec A_3 \prec A_1$	A_1

Some conclusions can be drawn from Table 10 as follows: when the attitude of experts is neutral ($\kappa=1$), the value of risk appetite τ cannot affect the ranking order of ESTs with optimal alternative remaining A_7, but influence the values of $\theta(A_i)$ to better rank. When the attitude of experts is pessimistic ($\kappa=\frac{1}{2}$), the value of $\theta(A_i)$ is slightly less than neutral-decision, but the ranking order remains unchanged with different values of τ with optimal alternative remaining A_7. It is noted that when the attitude of experts is optimistic ($1<\kappa\leq 2$), the values of $\theta(A_i)$ increase significantly and risk appetite of experts τ may cause different ranking results: $A_6 \prec A_5 \prec A_2 \prec A_4 \prec A_3 = A_7 \prec A_1$ ($\tau=\frac{1}{4},\kappa=\frac{3}{2}$) and $A_2 \prec A_7 \prec A_4 \prec A_5 \prec A_6 \prec A_3 \prec A_1$ ($\tau=\frac{1}{4},\tau=\frac{1}{2};\kappa=2$). The obtained orders are reversed since alternative A_1 outperforms A_7 compared to those under neutral and pessimistic situations. Therefore, it is quite necessary to establish a suitable combination of risk appetite and optimism preference parameters for reducing decision risk and avoiding loss, which can provide a worthwhile reference for stakeholders.

5.2.3. Comparative analysis

To verify the reliability of the ranking outcome deduced by the proposed approach, other widely used MCDM approaches for unbalanced linguistic terms, such as TOPSIS, TODIM, and MULTIMOORA are utilized for comparison. In consideration of comparability, the weights of criteria derived by the proposed method are applied in all MCDM approaches. The numerical example in Section 5 is conducted by these methods and ranking outcomes derived by different MCDM methods are presented in Table 11. The adopted methods are depicted in detail as follows:

(1) Nie et al. [56] adopted LDA as information representation and developed a multistage decision support framework integrating BWM, DEMATEL and TOPSIS method to derive the optimal alternative. The final ranking is yielded by deriving the closeness coefficient value of each alternative as $A_6 \prec A_4 \prec A_3 \prec A_1 \prec A_5 \prec A_2 \prec A_7$. Clearly, there is slight difference between the ranking result with that of the proposed method.

(2) Yu et al. [40] allowed the experts to elicit their linguistic assessments by unbalanced linguistic terms and the classical TODIM was extended to prioritize the available technology according to the proposed formulae of gain and loss under unbalanced LDA environment. To observe the influence of the attenuation factor on outcomes, the factor values are assigned as 1.5 and 2.5, separately, the ranking results are shown in Table 11.

(3) Liao et al. [57] integrated ORESTE method into UHFL-MULTIMOORA to consolidate three subordinate ranks of each alternative to get a comprehensive ranking, i.e. UHFL ratio system ranking: $A_6 \prec A_4 \prec A_2 \prec A_1 \prec A_3 \prec A_5 \prec A_7$, UHFL reference point ranking: $A_3 \prec A_5 \prec A_1 \prec A_2 \prec A_7 \prec A_4 \prec A_6$, and UHFL full Multiplicative Form ranking: $A_6 \prec A_4 \prec A_2 \prec A_1 \prec A_3 \prec A_5 \prec A_7$, the global ranking can be aggregated as $A_6 \prec A_2 \prec A_3 \prec A_4 \prec A_1 \prec A_5 \prec A_7$.

Table 11

Ranking results with different MCDM methods.

Technologies	Proposed Approach	BWM-LDA -TOPSIS	unbalanced-LDA-TODIM ($\Phi = 1.5$)	unbalanced-LDA-TODIM ($\Phi = 2.5$)	unbalanced HFL-MULTIMOORA
A_1	4	4	4	4	3
A_2	3	2	5	5	2
A_3	5	5	3	3	4
A_4	6	6	6	6	5
A_5	2	3	2	2	2
A_6	7	7	7	7	7
A_7	1	1	1	1	1
SCC	1.0	0.96	0.86	0.86	0.93

From Table 11, while the ranking result of other methods have not completely agreement with that of the proposed method, it is apparent that A_7 is always the best alternative, and A_6 is the worst alternative compared to other alternatives. To implement an effective comparison, we calculate Spearman's correlation coefficients (SCC) to demonstrate the statistical significance of the difference between the rankings of the proposed method and other methods as shown in Table 11. The average SCC value is 0.90 demonstrating that a high degree of linear correlation exists between ranking results and further certifies the reliability of the proposed method to some extent. For clarity, the ranking results derived by the proposed and the existing methods mentioned-above are depicted in Fig. 10.

Previous three examples verify the feasibility and effectiveness of the developed method in this paper. Compared to the three methods mentioned above, the merits of our method can be concluded as follows: Firstly, our method provides experts with great flexibility to elicit their evaluation towards ESTs with multi-granular UHFLTSs close to the human cognition. Secondly, Yu et al. [40] directly gave the weights of criteria and Liao et al. [57] derived the weights of criteria from the experts' preference matrices. Whereas, we combine the UHFLS- BWM and maximum deviation method to give the hybrid criteria weights, which enables the developed method more realistic. Finally, the expert weights are determined by a bi-objective optimization which is constructed by calculating the shortest distance from the LDPIS and the farthest distance from the LDNIS. Subsequently, double parameters TOPSIS method could concentrate on preference of alternatives and risk appetites of stakeholders.

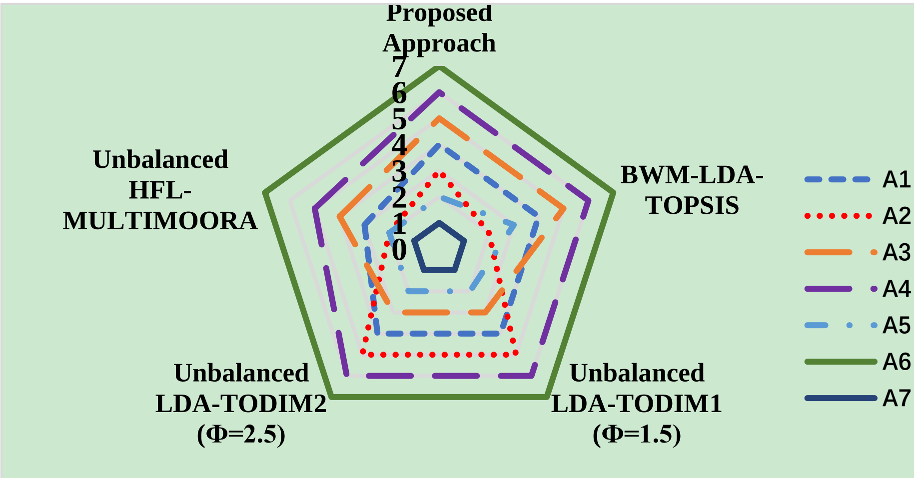


Fig. 10. Comparison of the ranking results derived by different methods.

6. Conclusions

Due to the production intermittency of electricity generated by renewable wind source, it is vital to identify the appropriate EST(s) for balancing energy reserves and promoting the transmission efficiency. Individual ESTs have their own specific technical and non-technical features and they are part of a wider socio-technical system. Therefore, this paper proposes a favorable multistage decision support framework to prioritize EST(s) for wind power with multi-granular UHFLTSs. The proposed framework of our study is insightful for comprehensive evaluation of EST concerning economic, social, technical and environmental factors and the main contributions are concluded as follows:

(1) Instead of employing a single and uniform form of linguistic expression, multi-granular

UHFLTSs are involved to cater to the needs of experts in expressing their assessments in a more flexible and accurate way when evaluating ESTs.

(2) To obtain a reasonable criteria weight, we extend classic BWM method with multi-granular UHFLTSs information to derive subjective weight. Incorporated with the maximum deviation method, the hybrid criteria weight is further distinguished.

(3) An innovative approach of deriving experts' weights based on double parameters TOPSIS under multi-granular UHFLTSs environment is proposed. A closeness degree optimization model is constructed for simultaneously deriving optimal stakeholders' weights and prioritize ESTs considering the risk appetites and optimism preferences of stakeholders.

(4) This MCGDM framework is conducted to manage EST selection problem with an empirical case. The sensitivity analysis demonstrates the ranking stability when facing different criteria weights and the impact of risk appetites as well as optimum coefficients of stakeholders on the outcomes. The comparison to other methods verifies the feasibility and practicality of our proposal.

Our proposal can effectively improve the rationality and precision in the EST selection process and contribute to the adoption of renewable energy to provide universal access to clean, reliable and affordable energy services. The EST(s) evaluation and selection framework in this study can be easily extended to cope with other complicate optimal selection problems of uncertainty in various fields especially under the multiexpert, multicriteria, and multipreference scenario, i.e. emergency decision making, renewable energy evaluation and optimal site selection of waste-to-energy plant. The limitations of this study are that in the case study, the dependences and interactions among these evaluation criteria should be investigated and more experts can be involved for reasonable decision making results. In future research, we will focus on integrating our methods to large-scale decision analysis procedure, especially for clustering method and consensus reaching process, which is more realistic in real-world problems.

Acknowledgments

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Appendix A

Table A.1

The semantics and numerical values of the linguistic terms for e_1.

Linguistic terms	Semantics	Numerical values
s_0^1: poor	$T(0,0,0.325)$	0
s_1^1: slightly poor	$T(0,0.325,0.5)$	0.325
s_2^1: fair	$T(0.325,0.5,0.675)$	0.5
s_3^1: slightly good	$T(0.5,0.675,1)$	0.675
s_4^1: good	$T(0.675,1,1)$	1

Table A.2

The semantics and numerical values of the linguistic terms for e_2.

Linguistic terms	Semantics	Numerical values
s_0^2: very poor	$T(0,0,0.3)$	0
s_1^2: poor	$T(0,0.3,0.45)$	0.3
s_2^2: slightly poor	$T(0.3,0.45,0.5)$	0.45
s_3^2: fair	$T(0.45,0.5,0.65)$	0.5
s_4^2: slightly good	$T(0.5,0.65,0.85)$	0.65
s_5^2: good	$T(0.65,0.85,1)$	0.85
s_6^2: extremely good	$T(0.85,1,1)$	1

Table A.3

The semantics and numerical values of the linguistic terms for e_3.

Linguistic terms	Semantics	Numerical values
s_0^3: extremely poor	$T(0,0,0.25)$	0
s_1^3: very poor	$T(0,0.25,0.35)$	0.25
s_2^3: poor	$T(0.25,0.35,0.4)$	0.35
s_3^3: slightly poor	$T(0.35,0.4,0.5)$	0.4
s_4^3: fair	$T(0.4,0.5,0.55)$	0.5
s_5^3: slightly good	$T(0.5,0.55,0.625)$	0.55
s_6^3: good	$T(0.55,0.625,0.75)$	0.625
s_7^3: very good	$T(0.625,0.75,1)$	0.75
s_8^3: extremely good	$T(0.75,1,1)$	1

Table A.4

Linguistic variables and consistency indexes for e_1.

Linguistic variables	Equally important ($\bar{s}_0^1$)	Less important ($\bar{s}_1^1$)	Medium important ($\bar{s}_2^1$)	Very important ($\bar{s}_3^1$)	Absolutely important ($\bar{s}_4^1$)
Semantics	*T*(1,1,1)	*T*(1,1,1.5)	*T*(1,1.5,3)	*T*(1.5,3,4)	*T*(3,4,5)
CIs	3	3.14	4.06	5.88	7.37

Table A.5

Linguistic variables and consistency indexes for e_2.

Linguistic variables	Equally important ($\bar{s}_0^2$)	Weakly important ($\bar{s}_1^2$)	Less important ($\bar{s}_2^2$)	Medium important ($\bar{s}_3^2$)	Really important ($\bar{s}_4^2$)	Very important ($\bar{s}_5^2$)	Absolutely important ($\bar{s}_6^2$)
Semantics	*T*(1,1,1)	*T*(1,1,1.5)	*T*(1,1.5,2)	*T*(1.5,2,2.5)	*T*(2,2.5,4)	*T*(2.5,4,5.5)	*T*(4,5.5,7)
CI	3	3.14	3.80	4.56	5.53	7.37	9.35

Table A.6

Linguistic variables and consistency indexes for e_3.

Linguistic variables	Equally important ($\bar{s}_0^3$)	Very weakly important ($\bar{s}_1^3$)	Weakly important ($\bar{s}_2^3$)	Less important ($\bar{s}_3^3$)	Medium important ($\bar{s}_4^3$)	Really important ($\bar{s}_5^3$)	Very important ($\bar{s}_6^3$)	Very very important ($\bar{s}_7^3$)	Absolutely important ($\bar{s}_8^3$)
Semantics	*T*(1,1,1)	*T*(1,1,2)	*T*(1,2,3)	*T*(2,3,4)	*T*(3,4,5)	*T*(4,5,6.5)	*T*(5,6.5,7)	*T*(6.5,7,8)	*T*(7,8,9)
CI	3	3.27	4.56	6.00	7.37	8.81	10.43	14.29	12.53

Table A.7

The initial multi-granular UHFLTSs decision matrices of three experts

Experts	Technologies	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}	C_{11}	C_{12}
e_1	A_1	$\{s_2^1,s_3^1\}$	$\{s_0^1,s_1^1,s_2^1\}$	$\{s_4^1\}$	$\{s_2^1,s_3^1\}$	$\{s_3^1,s_4^1\}$	$\{s_1^1,s_2^1\}$	$\{s_2^1,s_3^1,s_4^1\}$	$\{s_2^1,s_3^1\}$	$\{s_2^1\}$	$\{s_3^1,s_4^1\}$	$\{s_1^1,s_2^1\}$	$\{s_3^1\}$
	A_2	$\{s_1^1,s_2^1\}$	$\{s_2^1\}$	$\{s_3^1,s_4^1\}$	$\{s_3^1\}$	$\{s_0^1,s_1^1,s_2^1\}$	$\{s_2^1,s_3^1\}$	$\{s_3^1,s_4^1\}$	$\{s_4^1\}$	$\{s_2^1,s_3^1\}$	$\{s_1^1,s_2^1,s_3^1\}$	$\{s_3^1\}$	$\{s_2^1,s_3^1\}$
	A_3	$\{s_3^1,s_4^1\}$	$\{s_1^1,s_2^1\}$	$\{s_2^1\}$	$\{s_1^1,s_2^1,s_3^1\}$	$\{s_2^1,s_3^1\}$	$\{s_3^1\}$	$\{s_4^1\}$	$\{s_2^1,s_3^1,s_4^1\}$	$\{s_0^1,s_1^1,s_2^1\}$	$\{s_2^1,s_3^1\}$	$\{s_2^1\}$	$\{s_3^1\}$
	A_4	$\{s_1^1,s_2^1\}$	$\{s_3^1,s_4^1\}$	$\{s_0^1,s_1^1,s_2^1\}$	$\{s_2^1,s_3^1\}$	$\{s_3^1\}$	$\{s_2^1\}$	$\{s_0^1,s_1^1,s_2^1\}$	$\{s_3^1,s_4^1\}$	$\{s_2^1,s_3^1\}$	$\{s_3^1\}$	$\{s_4^1\}$	$\{s_2^1,s_3^1\}$
	A_5	$\{s_3^1\}$	$\{s_2^1,s_3^1,s_4^1\}$	$\{s_3^1,s_4^1\}$	$\{s_2^1,s_3^1\}$	$\{s_4^1\}$	$\{s_2^1,s_3^1\}$	$\{s_2^1,s_3^1\}$	$\{s_0^1,s_1^1\}$	$\{s_2^1\}$	$\{s_3^1\}$	$\{s_1^1,s_2^1,s_3^1\}$	$\{s_1^1,s_2^1\}$
	A_6	$\{s_0^1,s_1^1,s_2^1\}$	$\{s_2^1\}$	$\{s_2^1,s_3^1\}$	$\{s_3^1,s_4^1\}$	$\{s_3^1\}$	$\{s_1^1,s_2^1\}$	$\{s_3^1\}$	$\{s_2^1,s_3^1\}$	$\{s_3^1,s_4^1\}$	$\{s_1^1,s_2^1,s_3^1\}$	$\{s_0^1,s_1^1,s_2^1\}$	$\{s_2^1\}$
	A_7	$\{s_4^1\}$	$\{s_1^1,s_2^1\}$	$\{s_3^1,s_4^1\}$	$\{s_2^1,s_3^1\}$	$\{s_0^1,s_1^1,s_2^1\}$	$\{s_3^1\}$	$\{s_3^1,s_4^1\}$	$\{s_4^1\}$	$\{s_2^1,s_3^1\}$	$\{s_3^1\}$	$\{s_2^1,s_3^1,s_4^1\}$	$\{s_1^1,s_2^1\}$
e_2	A_1	$\{s_4^2,s_5^2\}$	$\{s_2^2,s_3^2\}$	$\{s_0^2,s_1^2,s_2^2\}$	$\{s_4^2,s_5^2\}$	$\{s_0^2,s_1^2,s_2^2\}$	$\{s_4^2,s_5^2,s_6^2\}$	$\{s_4^2\}$	$\{s_1^2,s_2^2,s_3^2\}$	$\{s_3^2,s_4^2\}$	$\{s_5^2\}$	$\{s_2^2,s_3^2\}$	$\{s_4^2,s_5^2\}$
	A_2	$\{s_5^2,s_6^2\}$	$\{s_5^2,s_6^2\}$	$\{s_5^2,s_6^2\}$	$\{s_3^2,s_4^2,s_5^2\}$	$\{s_2^2,s_3^2\}$	$\{s_3^2,s_4^2\}$	$\{s_2^2,s_3^2\}$	$\{s_3^2,s_4^2,s_5^2\}$	$\{s_0^2,s_1^2,s_2^2\}$	$\{s_5^2,s_6^2\}$	$\{s_3^2\}$	$\{s_3^2,s_4^2\}$
	A_3	$\{s_2^2,s_3^2,s_4^2\}$	$\{s_6^2\}$	$\{s_2^2,s_3^2\}$	$\{s_4^2,s_5^2,s_6^2\}$	$\{s_3^2,s_4^2\}$	$\{s_2^2,s_3^2,s_4^2\}$	$\{s_3^2\}$	$\{s_4^2,s_5^2,s_6^2\}$	$\{s_2^2,s_3^2\}$	$\{s_3^2,s_4^2\}$	$\{s_2^2,s_3^2,s_4^2\}$	$\{s_5^2\}$
	A_4	$\{s_3^2,s_4^2\}$	$\{s_4^2,s_5^2\}$	$\{s_1^2,s_2^2,s_3^2\}$	$\{s_5^2,s_6^2\}$	$\{s_2^2,s_3^2\}$	$\{s_4^2,s_5^2,s_6^2\}$	$\{s_5^2,s_6^2\}$	$\{s_2^2,s_3^2\}$	$\{s_4^2,s_5^2\}$	$\{s_3^2\}$	$\{s_3^2,s_4^2\}$	$\{s_4^2\}$
	A_5	$\{s_4^2,s_5^2,s_6^2\}$	$\{s_3^2,s_4^2\}$	$\{s_4^2,s_5^2\}$	$\{s_2^2,s_3^2\}$	$\{s_2^2,s_3^2,s_4^2\}$	$\{s_2^2,s_3^2\}$	$\{s_2^2,s_3^2,s_4^2\}$	$\{s_5^2\}$	$\{s_2^2,s_3^2\}$	$\{s_5^2,s_6^2\}$	$\{s_3^2,s_4^2,s_5^2\}$	$\{s_4^2,s_5^2\}$
	A_6	$\{s_2^2,s_3^2\}$	$\{s_4^2,s_5^2\}$	$\{s_3^2,s_4^2,s_5^2\}$	$\{s_3^2,s_4^2,s_5^2\}$	$\{s_3^2,s_4^2\}$	$\{s_2^2,s_3^2,s_4^2\}$	$\{s_5^2\}$	$\{s_3^2,s_4^2\}$	$\{s_2^2,s_3^2,s_4^2\}$	$\{s_2^2,s_3^2\}$	$\{s_5^2,s_6^2\}$	$\{s_5^2,s_6^2\}$
	A_7	$\{s_3^2,s_4^2,s_5^2\}$	$\{s_5^2\}$	$\{s_5^2,s_6^2\}$	$\{s_5^2,s_6^2\}$	$\{s_3^2,s_4^2,s_5^2\}$	$\{s_2^2,s_3^2,s_4^2\}$	$\{s_3^2,s_4^2\}$	$\{s_3^2\}$	$\{s_4^2,s_5^2\}$	$\{s_5^2\}$	$\{s_0^2,s_1^2,s_2^2\}$	$\{s_2^2,s_3^2\}$
e_3	A_1	$\{s_5^3\}$	$\{s_2^3,s_3^3\}$	$\{s_7^3\}$	$\{s_4^3,s_5^3,s_6^3\}$	$\{s_3^3,s_4^3\}$	$\{s_4^3\}$	$\{s_3^3,s_4^3,s_5^3\}$	$\{s_6^3\}$	$\{s_3^3,s_4^3\}$	$\{s_5^3,s_6^3\}$	$\{s_2^3,s_3^3\}$	$\{s_4^3\}$
	A_2	$\{s_7^3\}$	$\{s_6^3\}$	$\{s_6^3,s_7^3\}$	$\{s_3^3,s_4^3\}$	$\{s_4^3,s_5^3\}$	$\{s_5^3\}$	$\{s_2^3,s_3^3\}$	$\{s_4^3,s_5^3\}$	$\{s_6^3,s_7^3\}$	$\{s_7^3\}$	$\{s_6^3\}$	$\{s_2^3,s_3^3,s_4^3\}$
	A_3	$\{s_3^3\}$	$\{s_6^3,s_7^3\}$	$\{s_2^3\}$	$\{s_5^3,s_6^3\}$	$\{s_3^3,s_4^3,s_5^3\}$	$\{s_2^3,s_3^3\}$	$\{s_5^3,s_6^3,s_7^3\}$	$\{s_3^3,s_4^3,s_5^3\}$	$\{s_7^3\}$	$\{s_6^3\}$	$\{s_4^3,s_5^3\}$	$\{s_2^3,s_3^3\}$
	A_4	$\{s_2^3,s_3^3,s_4^3\}$	$\{s_5^3\}$	$\{s_5^3,s_6^3\}$	$\{s_4^3\}$	$\{s_6^3,s_7^3\}$	$\{s_7^3\}$	$\{s_2^3,s_3^3,s_4^3\}$	$\{s_4^3\}$	$\{s_0^3,s_1^3,s_2^3\}$	$\{s_3^3,s_4^3\}$	$\{s_5^3\}$	$\{s_6^3\}$
	A_5	$\{s_6^3\}$	$\{s_3^3,s_4^3,s_5^3\}$	$\{s_2^3,s_3^3\}$	$\{s_4^3,s_5^3\}$	$\{s_7^3\}$	$\{s_6^3,s_7^3\}$	$\{s_3^3,s_4^3\}$	$\{s_5^3,s_6^3,s_7^3\}$	$\{s_2^3,s_3^3\}$	$\{s_6^3\}$	$\{s_5^3\}$	$\{s_5^3\}$
	A_6	$\{s_5^3,s_6^3,s_7^3\}$	$\{s_3^3,s_4^3\}$	$\{s_0^3,s_1^3,s_2^3\}$	$\{s_6^3\}$	$\{s_4^3\}$	$\{s_4^3,s_5^3\}$	$\{s_7^3\}$	$\{s_2^3,s_3^3,s_4^3\}$	$\{s_6^3,s_7^3\}$	$\{s_4^3,s_5^3\}$	$\{s_5^3\}$	$\{s_4^3\}$
	A_7	$\{s_3^3,s_4^3,s_5^3\}$	$\{s_2^3,s_3^3\}$	$\{s_7^3\}$	$\{s_6^3\}$	$\{s_5^3,s_6^3\}$	$\{s_2^3,s_3^3,s_4^3\}$	$\{s_4^3\}$	$\{s_2^3,s_3^3\}$	$\{s_5^3,s_6^3\}$	$\{s_0^3,s_1^3,s_2^3\}$	$\{s_6^3\}$	$\{s_4^3,s_5^3,s_6^3\}$

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