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A Multi-Criteria Decision-Making Approach for Energy Storage Technology Selection Based on Demand

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Abstract: Energy storage technologies can reduce grid fluctuations through peak shaving and valley filling and effectively solve the problems of renewable energy storage and consumption. The application of energy storage technologies is aimed at storing energy and supplying energy when needed according to the storage requirements. The existing research focuses on ranking technologies and selecting the best technologies, while ignoring storage requirements. Here, we propose a multi-criteria decision-making (MCDM) framework for selecting a suitable technology based on certain storage requirements. Specifically, we consider nine criteria in four aspects: technological, economic, environmental, and social. The interval number, crisp number, and linguist terms can be transformed into a probabilistic dual hesitant fuzzy set (PDHFS) through the transformation and fusion method we proposed, and a suitable technology can be selected through distance measurements. Subsequently, the proposed method is applied in a representative case study for energy storage technology selection in Shanxi Province, and a sensitivity analysis gives different scenarios for elaboration. The results show that the optimal selection of energy storage technology is different under different storage requirement scenarios. The decision-making model presented herein is considered to be versatile and adjustable, and thus, it can help decision makers to select a suitable energy storage technology based on the requirements of any given use case.

Keywords: energy storage technology; technology selection; multi-criteria decision making; probabilistic dual hesitant fuzzy set; storage requirement

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1. Introduction

Traditional fossil fuels such as coal, oil, and natural gas are the most prominent sources of energy in the 21st century. The use of traditional fossil energy has promoted global economic development; however, it has also caused serious environmental problems. For example, the burning of fossil fuels produces a large amount of carbon dioxide, which is the main cause of the greenhouse effect. Consequently, new energy and renewable energy with abundant resources and low environmental pollution footprints have progressed significantly. The development of renewable energy is fundamental to reduce carbon dioxide emissions and solve environmental problems, and it is an important strategy recognized by countries all over the world to deal with atmospheric pollution and resource depletion. However, the development of renewable energy has faced challenges and limitations. Renewable energy-based energy generation depends on the availability of natural resources, which is volatile and intermittent. These characteristics make it difficult to adjust and control power generation, and also affect the safe and stable operation of the power grid. Therefore, nowadays, storage of energy is a key issue in the development of renewable energy.

In more detail, large-scale energy storage technology, which can solve the problems of randomness and the volatility of power generation, is an effective measure to solve such problems encountered in the current development of renewable energy, with similar solutions being applied across the electricity chain, i.e., from the stage of power generation to the distribution of electricity to end-users. It can be used as emergency energy and can also be used for peak shaving and valley filling to reduce grid fluctuations. However, different storage technologies show different characteristics in terms of technological, economic, social, and environmental aspects, and can satisfy different storage requirements. The development of new and renewable energy features different implications and requirements for different geographical areas and contexts, and the selection of technology needs to consider such requirements throughout the different development stages of such transitions. Hence, the question of how to select a suitable energy storage technology on the basis of the development of renewable energy is a key issue in energy planning, and it is also a prerequisite for solving energy security problems [1].

Specifically, energy storage technology selection needs to achieve multiple goals and consider many factors, including economic, technological, social, and environmental. Different approaches are used to optimize the selection of energy storage technologies, with some of them using state of the art practices, e.g., machine learning techniques [2–6], while other scholars use multi-objective optimization methods for technology selection [7]. However, various aspects often conflict with each other. For example, technologies that introduce lower levels of pollution are usually more expensive. This makes it difficult for decision makers to directly select a suitable storage technology. With this in mind, the energy storage technology selection problem, involving numerous fuzzy factors, can be formulated as an MCDM problem, with the pros and cons of decision variables often requiring the use of interval numbers, crisp numbers, and linguistic terms expressed in natural language. MCDM methods are commonly used in the field of energy research, such as renewable energy siting [8], solar power plant location selection [9], photovoltaic system selection [10], and selection of suitable locations for wind and solar farms [11,12]. T. Chen et al. used the MCDM approach to select a suitable renewable energy source (RES) alternative [13], and Şengül et al. ranked renewable energy supply and selected priority renewable energy [14]. Some scholars have combined MCDM methods with other methods such as the analytic hierarchy process (AHP), the technique for order preference by similarity to an ideal solution (TOPSIS), and geographic information systems (GIS) [11,12,15]. Actually, it can be argued that most of the existing literature combines the MCDM method and other methods for ranking the alternatives and selecting the best ranking energy storage technology. However, an important factor for energy storage selection which is ignored in the above literature is the requirements that storage technologies are used to fulfill. The purpose of energy storage is to meet storage requirements; both excessive and insufficient storage are unreasonable and may result in non-viable investments. Therefore, energy storage requirements should be considered in the selection of energy storage technology. Consequently, this paper proposes an MCDM energy storage approach for selecting a suitable energy storage technology considering the power storage requirements.

The combination of the fuzzy method and MCDM is an effective way to solve the problem recognized by many scholars. On the basis of the above analysis, the selection of energy storage is in a fuzzy environment and needs to consider the energy storage requirement, which is hard to concretely express. Therefore, combining the MCDM and fuzzy method to solve the problem of energy storage technology selection is an effective method. The methods commonly used by scholars in fuzzy areas are intuitionistic fuzzy numbers, type-2 fuzzy sets [9], neutrosophic fuzzy numbers [16], dual hesitant fuzzy sets [7], and triangular interval-valued fuzzy numbers [17]. Zhang et al. use dual hesitant fuzzy sets to express the characteristics of storage technologies and generate the relevant assessment [18]. A. Barin et al. and J. Ren proposed a method on the basis of AHP and fuzzy sets for ranking and selecting storage technologies [19,20]. However, the number of technologies and criteria in those studies is limited. What is more, the above body of literature does not take into account probability in the decision, while the probability information has an impact on the decision-making results. This study aims to construct an MCDM approach based on probabilistic dual hesitant fuzzy sets (PDHFSs) and construct a framework for the selection of energy storage technology. This study comes with two contributions: (1) the design of the transformation and fusion method for real (crisp) numbers to probabilistic dual intuitionistic fuzzy numbers; (2) the proposal of a framework for selecting the energy storage technology based on energy storage requirements and provide an orientation for future research as well as suggestions and references for decision makers to make decisions and policies.

This study is organized as follows: the background of energy storage technology development and the problems in existing studies are introduced in Section 1. Section 2 describes the energy storage technologies and characteristics of these technologies. Section 3 discusses the evaluation criteria and gives the characteristics of energy storage technologies based on the analysis of recent literature. The MCDM methodology and the decision-making framework are explained in Section 4. In Section 5, the case study and scenarios analysis are presented to illustrate the approach of this paper. Finally, the conclusions and directions for further research are presented in Section 6.

2. Energy Storage Technologies

There are many classification standards for energy storage technology, such as the storage method, storage duration, response time, etc. [21–23]. The most popular method in the above classifications which has been recognized by many scholars is the form of storage [23]. According to the form of storage, technologies can be classified into mechanical, electrochemical, chemical, electrical, and thermochemical [18,21].

Mechanical storage is the most common storage technology, and the installed capacity of mechanical energy storage accounts for more than 90% of the total capacity [20]. Technologies that belong to this category mainly include pumped hydro storage (PHS), compressed air energy storage (CAES), and flywheel energy storage (FES). Electrochemical storage includes lead–acid, lithium-ion (Li-ion), nickel–cadmium [24], etc. Among them, Li-ion and lead–acid occupy the majority of market shares [25]. Chemical storage technologies include hydrogen and synthetic natural gas technology [26]. Of the two technologies, hydrogen storage technology is the most important chemical storage technology. Electrical storage includes capacitors and superconducting magnetic energy storage (SMES) [27]. Based on the above, this study considers nine technologies in five categories as follows:

- PHS, CAES and FES (mechanical storage);
- Li-ion and lead-acid (electrochemical storage);
- Hydrogen (chemical storage);
- Capacitors and SMES (electrical storage);
- Thermochemical.

3. Evaluation Criteria for Energy Storage Technologies

Some influencing factors should be considered when selecting the suitable technology. These factors are divided into four categories: technological factors [7,18], economic factors [20], environmental factors, and social factors, as shown in Table 1. From a technological perspective, indicators are used to express the characteristics of technologies, which include storage capacity, response time, lifetime, energy and power density, risk and safety, energy efficiency, and energy intensity. The references for these factors are shown in Table 1. Among these indicators, some are difficult to express with a specific value, such as storage capacity, which indicates the maximum amount of electricity that the energy storage technology can store. Excluding these indicators, we select some representative indicators, including energy efficiency, response time, lifetime, energy density, and self-discharge losses as the technological factors in the MCDM. The energy efficiency was used to measure the degree of energy utilization. Response time measures the time required for the system to react and be able to supply electricity; it can usually be measured in minutes and seconds. Lifetime is a period in which energy storage technology equipment can operate. Energy density measures the amount of energy per unit of a size of the installation, and the unit of this index is Wh/kg which is the unit of weight. Self-discharge losses indicate the energy lost during a period in which the system remains idle.

Table 1. Evaluation criteria for energy storage technologies and the literature source.

Aspects	Factors	References
Technological	Lifetime	[7,18,28–31]
	Storage capacity	[7,16,29,30]
	Response time	[7,16,18]
	Energy density	[7,18,28–31]
	Risk/safety	[29,30]
	Energy efficiency	[28,30]
	Energy intensity	[28,30]
	Self-discharge losses	[3]
Economic	Input cost	[1]
	Investment costs	[16,28,29,32]
	Operation costs	[16,18,28–32]
	Economic benefits	[7,30]
	Power capital cost	[22,33,34]
	Energy capital cost	[22,27,34–36]
Environmental	Emissions	[7,29–31]
	CO_2 intensity	[28–30]
	Stress on ecosystem	[1]
	Protection of the environment	[7]
	Resource consumption	[29]
	Land use	[4]
Social	Job creation	[7,16,29]
	Social acceptance	[7,29]
	Health and safety	[29,31]
	Government incentive	[4]

Economic factors include input cost, investment costs, operation costs, economic benefits, power capital cost and energy capital cost. These factors are mainly from the perspective of economic cost to measure the economic characteristics of technology. This paper selects two representative indicators among these factors: power capital cost and energy capital cost, to represent the economic characteristics. Environmental factors include emissions, CO_2 intensity, stress on ecosystems, protection of the environment, resource consumption, and land use. However, some indicators are difficult to measure because the lifetime of energy storage technologies is difficult to determine; therefore, referring to [18], we comprehensively consider the environmental impact to evaluate the energy storage technology. Social factors include job creation, social acceptance, government incentives, and health and safety. Taking these factors into consideration, we selected social acceptance to express social characteristics.

Following the determination of parameters involved in the problem, in this paper, storage is applied to power generation and distribution, with energy transformations also included in the evaluation process. Subsequently, by considering the above, the respective value ranges are shown in Table 2.

Table 2. The characteristics and relevant value ranges of energy storage technologies.

Technologies	Energy Efficiency (%)	Response Time	Lifetime (years)	Energy Density (Wh/kg)	Self-Discharge Losses (%/day)	Power Capital Cost (USD/kw)	Energy Capital Cost (USD/kwh)	Environmental Dimension	Social Acceptance
PHS	(65, 75) [37], (75, 80) [38]	Seconds–minutes [36]	(30, 60) [34]	(0.5, 1.5) [18,27]	(0.0001, 0.0001) [18]	(700, 2000) [33], (600, 2000) [27], (500, 4600) [39]	(5, 100) [27], (5, 430) [40]	Very high [18]	Very high, high
CAES	(41, 75) [23]	Minutes [36]	(20, 40) [22]	(30, 60) [18] [27]	(0.0001, 0.0001) [18]	(400, 800) [34]	(50, 150) [35],	Very high [18]	Very high, high
FES	85 [41], (80, 90) [23]	Seconds [36]	(15, 20) [34],	(10, 30) [27], (5, 130) [18]	(20,100) [18]	(250, 350) [27]	(1000, 5000) [35]	Very high [18]	Very high, high
Lead–acid	(70, 80) [42], (75, 80) [37]	<Seconds [36]	(3, 12) [43]	(30, 50) [18]	(0.1,0.3) [22]	(300, 600) [34]	(150, 500) [44]	Very high [18]	Medium
Li-ion	(65, 75) [23], 78 [45]	Seconds [36]	(5, 15) [23],	(75, 200) [27], (75, 250) [18]	(0.1, 0.3) [22]	(1200, 4000) [23]	(600, 2500) [44]	Low [18]	High, Medium
Hydrogen	(35, 40) [46]	Minutes [44]	(5, 20), (5, 15) [22]	(800, 1000) [18]	(0.5, 2) [18]	(500, 10,000) [34]	(2, 15) [47]	High [18]	Medium, high
Super-capacitors	(85, 98) [48]	Milliseconds [49]	(10, 20) [34], 20+ [27]	(0.1, 15) [18], (2.5, 15) [27]	(20, 40) [22]	(100, 300) [22]	(300, 2000) [36]	Low [18]	Medium
SMES	(90, 95) [44],	Milliseconds	(20, 30) [34]	(0.5, 5) [27] [18]	(10, 15) [22]	(200, 300) [22]	(1000, 10,000) [22]	Very high [18]	Medium
Thermal (TES)	(14, 18) [50]	Not for rapid [44]	(5, 15) [22]	(30, 60) [22], <60 [51]	(0.05, 1) [22]	(100, 400) [35]	(3, 130) [52]	Low [22]	Medium

4. Methodology

Based on the above analysis, energy storage technology selection needs to achieve multiple goals, whereas various goals often conflict with each other. There are some criteria that should be considered in the process of selection [53]. In this section, an MCDM is proposed to select energy storage technology. First, fuzzy sets and PDHFSs are introduced to express the uncertain information. To compare the distance between two probabilistic dual hesitant fuzzy numbers (PDHFNs), a distance measurement is proposed. Subsequently, the transformation of the data is defined to transform certain data into a probabilistic dual hesitant fuzzy number. Next, the criteria weights and expert weights are calculated using the entropy method and maximizing deviation approach, respectively. Finally, the framework and steps for energy storage technology decision making are described.

4.1. Fuzzy Sets and Probabilistic Dual Hesitant Fuzzy Sets

The concept of fuzzy sets, which can avoid detailed uncertain information loss, was first proposed by Atanassov, and it contains the three dimensions of uncertainty: membership degree, non-membership degree, and hesitancy degree [54]. In order to describe the hesitation information more comprehensively, the hesitant fuzzy set (HFS) was proposed. Compared with fuzzy numbers, the HFS contains information regarding hesitant degree [55]. Moreover, to overcome the shortcomings of both the fuzzy set and HFS by expressing the uncertain information more accurately, the dual hesitant fuzzy set (DHFS) was proposed by Zhu et al. [56], which combines the characteristics of the fuzzy set and HFS. The definition [57] of the DHFS is:

Definition 1. *Let $X = \{x_1, x_2, \cdots, x_n\}$ be a universe of discourse for each $x \in X$. The DHFS D can be defined in Equation (1) as:*

$$Du = \left\{ \left\langle x, \widetilde{h}(x), \widetilde{g}(x) \right\rangle \middle| \, x \in X \right\}, \tag{1}$$

where $\widetilde{h}(x)$ is the membership degree function and $\widetilde{g}(x)$ is the non-membership degree function, and the degrees of these two value strictly satisfy $0 \leq \widetilde{h}(x) \leq 1$, $0 \leq \widetilde{g}(x) \leq 1$, and $0 \leq \widetilde{h}(x) + \widetilde{g}(x) \leq 1$.

On this basis, some scholars have further integrated the possibility of DHFS to express some preference information. For example, if the probability of membership is 0.2, and the probability of non-membership is 0.8. Thus, using preference information in the DHFS can describe uncertain information more comprehensively. For including probability information in the DHFS, the PDHFS was proposed by Hao et al. [58], as defined in the following:

Definition 2. *For every $x \in X$, PDHFS PD is defined in Equation (2):*

$$PD = \{\langle x, \widetilde{hp}(x), \widetilde{gp}(x)\rangle \big| x \in X\}, \tag{2}$$

where $\widetilde{hp}(x)$ is the membership function, and $\widetilde{gp}(x)$ is the non-membership function. Let $\gamma\big|p^h$ and $\varphi|p^g$ be the elements in $\widetilde{hp}(x)$ and $\widetilde{gp}(x)$, respectively. For every $x \in X$, $\gamma, \varphi \in [0,1]$. γ^+ and φ^+ are the maximum values in $\widetilde{hp}(x)$ and $\widetilde{gp}(x)$, respectively. Moreover, γ^+ and φ^+ satisfy $0 \le \gamma^+ + \varphi^+ \le 1$. p^h and p^g are the probabilities of γ and φ, respectively, and satisfy $0 \le p^h \le 1$, $0 \le p^g \le 1$, $\sum p^h \le 1$ and $\sum p^g \le 1$. $pd = \langle \widetilde{hp}(x), \widetilde{gp}(x)\rangle$ is the element of PDHFS, which is called PDHFN and is expressed as $pd = \left\langle \widetilde{hp}, \widetilde{gp}\right\rangle$.

Let $pd_1 = \left\langle \widetilde{hp}_1, \widetilde{gp}_1\right\rangle$ and $pd_2 = \left\langle \widetilde{hp}_2, \widetilde{gp}_2\right\rangle$ be two PDHFNs, and the operations of a PDHFN are [58]:

(1) $$pd_1 \oplus pd_2 = \bigcup_{\substack{\gamma_1|p_1^h \in \widetilde{hp}_1, \varphi_1|p_1^g \in \widetilde{gp}_1 \\ \gamma_2|p_2^h \in \widetilde{hp}_2, \varphi_2|p_2^g \in \widetilde{gp}_2}} \left\langle (\gamma_1 + \gamma_2 - \gamma_1\gamma_2)\Big|p_1^h p_2^h,\ \varphi_1\varphi_2\Big|p_1^g p_2^g\right\rangle$$

(2) $$pd_1 \otimes pd_2 = \bigcup_{\substack{\gamma_1|p_1^h \in \widetilde{hp}_1, \varphi_1|p_1^g \in \widetilde{gp}_1 \\ \gamma_2|p_2^h \in \widetilde{hp}_2, \varphi_2|p_2^g \in \widetilde{gp}_2}} \left\langle \gamma_1\gamma_2\Big|p_1^h p_2^h,\ (\varphi_1 + \varphi_2 - \varphi_1\varphi_2)\Big|p_1^g p_2^g\right\rangle$$

(3) $$\lambda pd_1 = \bigcup_{\substack{\gamma_1|p_1^h \in \widetilde{hp}_1, \varphi_1|p_1^g \in \widetilde{gp}_1 \\ \lambda > 0}} \left\langle (1 - (1-\gamma_1))^\lambda \Big| p_1^h,\ {\varphi_1}^\lambda\Big|p_1^g\right\rangle$$

The weight of each PDHFN may be different, and each PDHFN should be weighted using weighted averaging operators. Let $(pd_1, pd_2, \cdots, pd_n)$ be the vector of n PDHFNs, and use $W = (w_1, w_2, \cdots, w_n)$ to represent the weight vector, where each weight satisfies $w_j \ge 0$, and $\sum_{j=1}^{n} w_j = 1, j = 1,2,\cdots n$. The weighted averaging operator for the PDHFN is:

$$\begin{aligned} PDHFW(pd_1, pd_2, \cdots, pd_n) &= \bigoplus_{j=1}^{n} w_j pd_j \\ &= \bigcup_{\substack{\gamma_1|p_1^h \in \widetilde{hp}_1, \varphi_1|p_1^g \in \widetilde{gp}_1 \\ \gamma_2|p_2^h \in \widetilde{hp}_2, \varphi_2|p_2^g \in \widetilde{gp}_2}} \left\{ (1 - \prod_{i=1}^{n}(1-\gamma_i)^{w_i}) \Big| \prod_{i=1}^{n} p_i^h, \prod_{i=1}^{n} {\varphi_i}^{w_i} \Big| \prod_{i=1}^{n} p_i^g \right\}, j = 1,2,\cdots,n \end{aligned} \tag{3}$$

4.2. Distance Measurement for PDHFS

In the MCDM process, we should compare different alternatives and choose the one that is closest to the ideal solution. The smaller the distance, the closer the two PDHFNs are. To compare the alternatives which are expressed in a PDHFS, a distance measurement is proposed based on [59].

It is assumed that $M_A = \{1,2,\cdots,m_A\}$, $N_A = \{1,2,\cdots,n_A\}$, $N_B = \{1,2,\cdots,n_B\}$, $M_B = \{1,2,\cdots,m_B\}$, where $i \in M_A$, $j \in N_A$, $i' \in M_B$, and $j' \in N_B$. Then, let

$A = \left\{ \left(x, \widetilde{hp_{A_i}}(x), \widetilde{gp_{A_j}}(x) \right) \middle| x \in X \right\}$ and $B = \left\{ \left(x, \widetilde{hp_{B_{i'}}}(x), \widetilde{gp_{B_{j'}}}(x) \right) \middle| x \in X \right\}$ be two PDHFNs; the distance between A and B is defined by Garg and Kaur as [59]:

$$d(A,B) = \sum_{v=1}^{n} w_v \left(\sum_{k=1}^{n} \frac{1}{n} \left(\frac{\left| \frac{1}{M_A} \sum_{i=1}^{M_A} \left(\gamma_{A_i}(x_k) p^h_{A_i}(x_k) \right) - \frac{1}{M_B} \sum_{i'=1}^{M_B} \left(\gamma_{B'_i}(x_k) p^h_{B'_i}(x_k) \right) \right|^{\lambda}}{2} + \frac{\left| \frac{1}{N_A} \sum_{j=1}^{N_A} \left(\varphi_{A_j}(x_k) p^g_{A_j}(x_k) \right) - \frac{1}{N_B} \sum_{j'=1}^{N_B} \left(\varphi_{B'_j}(x_k) p^g_{B'_j}(x_k) \right) \right|^{\lambda}}{2} \right) \right)^{\frac{1}{\lambda}} \tag{4}$$

where $\gamma_{A_i} \in hp_{A_i}, \gamma_{B_{i'}} \in hp_{B_{i'}}, \varphi_{A_j} \in gp_{A_j}, \varphi_{B_{j'}} \in gp_{B_{j'}}$. Parameter λ is a real number, and the value of λ is usually assumed as 2 [60]. The distance, d, satisfies $0 \leq d(A,B) \leq 1$ [59].

4.3. Data Transformation and Fusion

The data we collected are usually of three types: interval numbers, crisp numbers, and linguistic terms, each of which needs to be converted. Decision makers should transform a certain value into uncertain data before the distance measurement. On the basis of the method proposed by Zhang et al. [18], the above three types of real numbers can be transformed to fuzzy numbers. The transformation approach of the three types of data is:

(1) Transformation of interval numbers

The interval number comprises the upper and lower bounds of the variable. Let the interval number be $a_{ij} = (a^L_{ij}, a^U_{ij})$, where i represents the i-th alternative, and j represents the j-th criteria. a^U_{ij} is the upper bound and a^L_{ij} is the lower bound of the variable. The unit of the initial value of every alternative may differ; thus, the initial interval number needs to be normalized first, as shown in Equation (5), before the transformation.

$$\begin{aligned} a^*_{ij} &= \left(\bar{a}^L_{ij}, \bar{a}^U_{ij} \right) \\ \bar{a}^L_{ij} &= \frac{a^L_{ij}}{\sqrt{\sum_{i=1}^{m} \left((a^L_{ij})^2 + (a^U_{ij})^2 \right)}}, \bar{a}^U_{ij} = \frac{a^U_{ij}}{\sqrt{\sum_{i=1}^{m} \left((a^L_{ij})^2 + (a^U_{ij})^2 \right)}} \end{aligned} \tag{5}$$

The transformation information was constructed by Guo [61], shown in Equation (6). Membership and non-membership are determined by the average and spread of the initial interval number. The greater the average, the greater the degree of membership, and the greater the interval number's spread, the greater the degree of non-membership. Consequently, following Equation (6), a fuzzy number is constructed.

$$\begin{aligned} &\alpha_{ij} = (h_{ij}, g_{ij}),\ i = 1,2,\cdots,mj = 1,2,\cdots,n \\ &h_{ij} = \bar{a}^L_{ij}, g_{ij} = 1 - \bar{a}^U_{ij} \end{aligned} \tag{6}$$

where $\alpha_{ij} = (h_{ij}, g_{ij})$ is the fuzzy number, and $\bar{a}^L_{ij}$ and $\bar{a}^U_{ij}$ are the normalized values of a^L_{ij} and a^U_{ij}, respectively.

(2) Transformation of crisp numbers

When the values of attributes are described in terms of crisp numbers, Equations (7) and (8) can be used for transformation. Equation (7) is the normalized function, and a^*_{ij} is the normalized value of a_{ij}. Following these two equations, we can transform the crisp numbers to fuzzy numbers.

$$a^*_{ij} = \frac{a_{ij}}{\sqrt{\sum_{i=1}^{m} a^2_{ij}}}, \tag{7}$$

$$\begin{array}{l}\alpha_{ij} = (h_{ij}, g_{ij}),\ i = 1, 2, \cdots, mj = 1, 2, \cdots, n \\ h_{ij} = a_{ij}^*, g_{ij} = 1 - a_{ij}^*\end{array} \quad (8)$$

(3) Transformation of linguistic terms

Sometimes, the value of attribute can only be expressed in linguistic terms, such as high/good, medium, and low/short; we should also consider the transformation of linguistic terms. Based on Guo [61], the linguistic terms can be divided into five levels, and each level has its corresponding fuzzy set, as shown in Table 3.

Table 3. The transformation for linguistic terms.

Linguistic Terms	(h_{ij}, g_{ij})
Very high, better, very long	(0.90, 0.10)
High, good, long	(0.75, 0.20)
Medium	(0.50, 0.45)
Low, bad, short	(0.35, 0.60)
Very low, worse, very short	(0.10, 0.90)

After the above transformation, interval numbers, crisp numbers, and linguistic terms can be transformed into fuzzy numbers. However, a PDHFS not only involves fuzzy information but also includes probability information. The probability should be added to the transformation process, and then, a PDHFS can be constructed based on fuzzy numbers. Due to the fact that probability information is difficult to calculate using a formula, probability information is usually given by an expert. Therefore, in the transformation, every expert should give the probability based on their preference, and the PDHFS can finally be formed.

4.4. Criteria Weights and Expert Weights Calculation

4.4.1. Criteria Weights Calculation

The importance of different criteria may be different, and the weight of criteria should be distinguished accordingly. We used the entropy weight method to calculate the weight of each criterion. The entropy value is used to judge the degree of dispersion of an index based on the definition of information entropy in this method. For a certain criterion, the smaller the value of the information entropy, the greater the degree of dispersion of the criterion, and the greater the weight of the criterion. The core part of the calculation with this method is to calculate the degree of difference between the criterion value and the average value of criteria. Thus, the average value of each criterion should be obtained before calculating the information entropy of each criterion. Based on the Equation (9), it can be calculated [62].

$$\begin{array}{l}\widetilde{pd}_j = \left\{ \left(\widetilde{\gamma}_j \middle| \widetilde{p}_j^h, \widetilde{\varphi}_j \middle| \widetilde{p}_j^g \right) \right\} \\ \widetilde{\gamma}_j = \frac{1}{m}\sum\limits_{i=1}^m \gamma_{ij}, \widetilde{\varphi}_j = \frac{1}{m}\sum\limits_{i=1}^m \varphi_{ij}, \widetilde{p}_j^h = \frac{1}{m}\sum\limits_{i=1}^m p_{ij}^h, \widetilde{p}_j^g = \frac{1}{m}\sum\limits_{i=1}^m p_{ij}^g\end{array} \quad (9)$$

Then, the information entropy of each criterion can be calculated using Equation (10):

$$e_j = -\frac{1}{\ln(m)}\sum_{i=1}^m \left[\frac{D(\widetilde{pd}_j, pd_{ij})}{\sum\limits_{i=1}^m D(\widetilde{pd}_j, pd_{ij})} \ln\left(\frac{D(\widetilde{pd}_j, pd_{ij})}{\sum\limits_{i=1}^m D(\widetilde{pd}_j, pd_{ij})}\right) \right], \quad (10)$$

where $D(\widetilde{pd}_j, pd_{ij})$ is the Euclidean distance, and the calculated formula [63] is shown in Equation (11):

$$D(pd_1, pd_2) = \sqrt{\left(\gamma_1 p_1^h - \gamma_2 p_2^h\right)^2 + \left(\varphi_1 p_1^g - \varphi_2 p_1^g\right)^2}, \quad (11)$$

Finally, based on Equation (12), the weight of each criterion can be calculated:

$$w_{ij} = \frac{1 - e_j}{\sum\limits_{j=1}^{m} (1 - e_j)}, \tag{12}$$

4.4.2. Expert's Weights Calculation

In the process of MCDM, experts from various related fields are invited to contribute to the evaluation. Because the experience and knowledge backgrounds of each expert are different, the weights of evaluation from each expert are correspondingly different; for example, the higher weight refers to the expert who has richer experience and knowledge. Thus, it is essential to generate the weight vectors of the experts. This study used the maximizing deviation measurement to calculate the experts' weights, as proposed by Xu and Cai [64]. The core of this approach is that the greater the deviation of the expert decision values, the greater the given weight; conversely, the smaller the deviation, the smaller the given weight. Therefore, the calculation formula is given by Equation (13):

$$\eta_k = \frac{\sum_{j=1}^{n} \sum_{i=1}^{m-1} \sum_{g=i+1}^{m} D(pd_{ij,k}, pd_{gj,k})}{\sum_{k=1}^{z} \sum_{j=1}^{n} \sum_{i=1}^{m-1} \sum_{g=i+1}^{m} D(pd_{ij,k}, pd_{gj,k})}, k = 1, 2, \cdots, z, \tag{13}$$

where η_k represents the kth expert weight, z is the number of experts, $D(pd_{ij,k}, pd_{gj,k})$ is the Euclidean distance, and the calculation formula is shown in Equation (11).

4.5. Decision Steps

The framework and steps of the decision-making model are presented in this section. Before the process starts, the decision makers make a first, rough selection of energy storage technologies based on the use case examined. We use m to indicate the number of energy storage technology alternatives, and $A = \{a_1, a_2, \cdots a_i, \cdots, a_m\}$ to indicate the set of alternatives, where $a_i \in A_i$ is the i-th energy storage technology. We let $C = \{c_1, c_2, \cdots c_j, \cdots, c_n\}$ be a set of criteria, and c_j present the j-th criteria, where $j = 1, 2, \cdots, n$. Let $W = \{w_1, w_2, \cdots w_j, \cdots, w_n\}$ denotes the weight of the criteria set, and w_j is the weight of c_j. For $\forall j \in n$, $0 \le w_j \le 1$ and $\sum_{j=1}^{n} w_j = 1$.

In addition, energy storage requirements need to be considered in the energy storage technology selection model. If decision makers ignore the requirements and blindly choose the energy storage technology, they may cause some issues which could not solve the problems of new and renewable energy storage. Thus, in the process of MCDM, a suitable energy storage technology should be selected based on the requirements information given by experts. The decision-making framework is shown in Figure 1, and the decision-making steps are:

Step 1: Establish the initial decision matrices based on the transformation and fusion method for interval numbers, crisp numbers, and linguistic terms in Section 4.3; every datum can be transformed into a PDHFN, and the decision matrices of each expert can be established.

Step 2: Determine the initial target matrix based on the requirement information; the initial target matrix can be established based on the transformation and fusion method in Section 4.3. Tm represents the target matrix and it is shown in Equation (14). In the matrix, tm_{kj} is the PDHFN obtained by the transformation of the k-th expert under the j-th criteria.

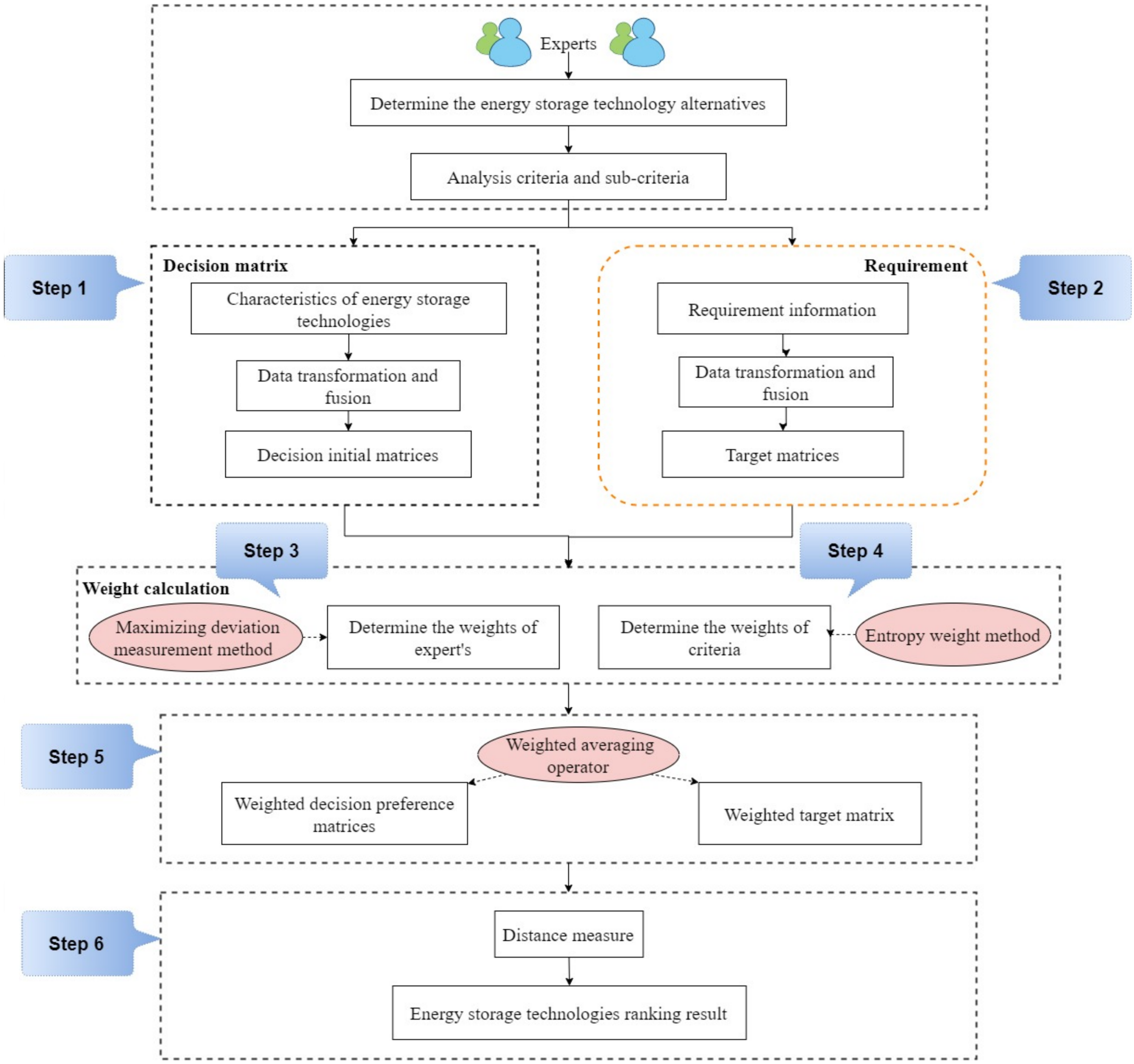

Figure 1. The decision-making framework for energy storage technology selection.

$$Dm = \begin{bmatrix} dm_{11} & dm_{12} & \cdots & dm_{1j} & \cdots & dm_{1n} \\ dm_{21} & dm_{22} & \cdots & dm_{2j} & \cdots & dm_{2n} \\ \vdots & \vdots & \cdots & \vdots & \cdots & \vdots \\ dm_{k1} & dm_{k2} & \cdots & dm_{kj} & \cdots & dm_{kn} \\ \vdots & \vdots & \cdots & \vdots & \cdots & \vdots \\ dm_{z1} & dm_{z2} & \cdots & dm_{zj} & \cdots & dm_{zn} \end{bmatrix}, \tag{14}$$

Step 3: Calculate criteria weights. Based on Equations (9)–(12), the weights of the criteria can be obtained, and the weight vector $W = \{w_1, w_2, \cdots w_j, \cdots, w_n\}$ can be obtained.

Step 4: Calculate the weight of each expert. Using the maximizing deviation approach based on Equation (13), the expert's weight vector $\eta = \{\eta_1, \eta_2, \cdots \eta_k, \cdots, \eta_z\}$ can be obtained.

Step 5: Calculate the weighted probabilistic dual hesitant fuzzy number (PDHFW). Based on the weighted averaging operator shown in Equation (3) and the weights of the criteria, a PDHFW for every alternative can be obtained.

Step 6: Distance calculation. Calculate the distance between the target matrix and the PDHFW based on Equation (4). The ranking result of energy storage technologies based on the distance calculation equation can be obtained, and the most suitable technology for the given storage requirements can be selected.

5. Case Study

This section presents the implications of the proposed approach for energy storage technology selection in Shanxi Province, China. China has put forward the goal of reducing carbon dioxide emissions by 2030 and striving to achieve carbon neutrality by 2060. The use of traditional fossil energy has caused air pollution, and thus the application of renewable energy is an effective way to reduce carbon dioxide emissions and solve the current problems. From the perspective of power structure, China's renewable energy power generation has been increasing since 2010, as shown in Figure 2. The 14th Five-Year Plan formulated by China in 2020 pointed out that it is necessary to promote the clean, low-carbon, safe, and efficient use of energy.

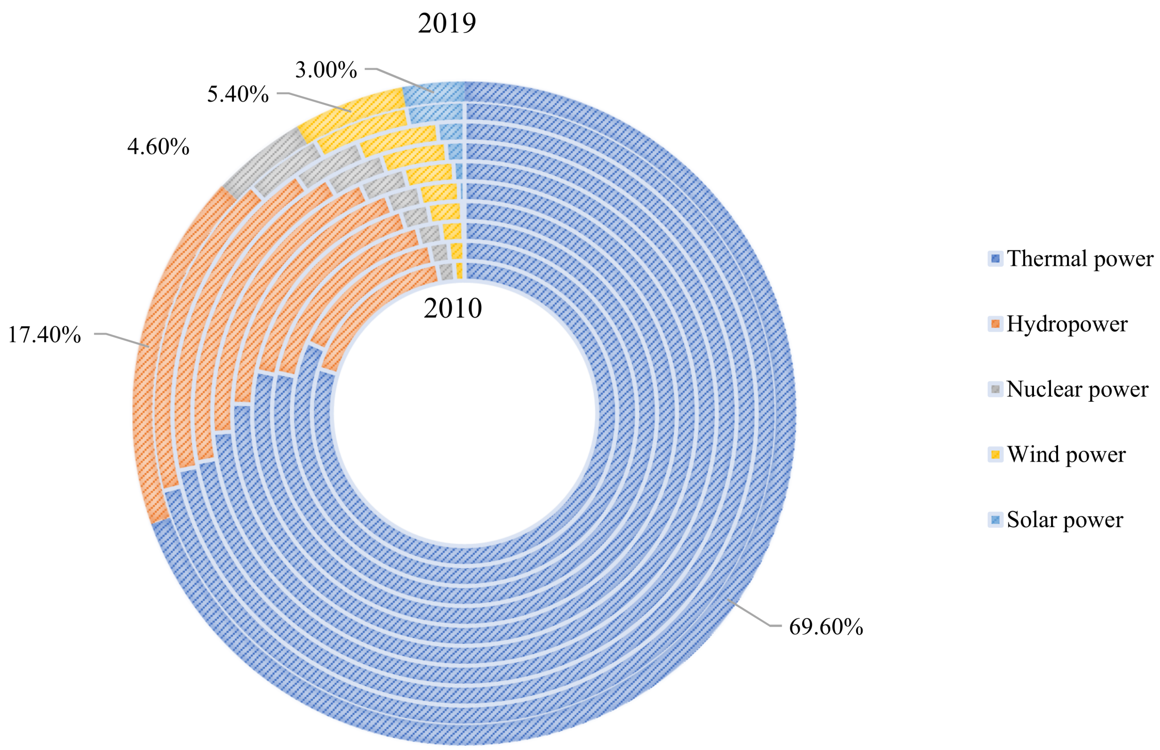

Figure 2. The composition of China's power generation from 2010 to 2019.

Shanxi Province is located in the west of Taihang mountain. The total area of the province is 156,000 km^2 and the province's permanent population was 37.292 million in 2020. Shanxi is the largest coal producing province in China, and its annual raw coal production has long been in the at forefront of the country's coal industry, accounting for more than a quarter of the total production. As a traditional coal-producing province in China, Shanxi Province actively implements energy structure transformation. Shanxi's annual electricity consumption was 4.98×10^7 MWh in 2020, and the proportion of renewable energy power generation has continued to increase. Figure 3 shows the utilization and development of some renewable energy sources. From Figure 3, we can see that the cumulative installed capacity of photovoltaic power, wind power, and biomass power continues to grow from 2015 to 2020. According to the data from the National Development and

Reform Commission of China, the share of renewable energy power generation increased from 11.21% in 2015 to 31.6% in 2020. In addition, the 14th Five-Year Renewable Energy Plan of Shanxi Province suggests that during the 14th Five-Year Plan period, Shanxi's investment in renewable energy will further increase, and by 2025, renewable energy power generation will account for 40% of the total power generation. At the same time, some renewable energy storage projects will be implemented with the development of renewable energy. For a renewable energy storage project, a decision-making approach for energy storage technology selection is necessary. This paper uses simulation to carry out model verification and case analysis.

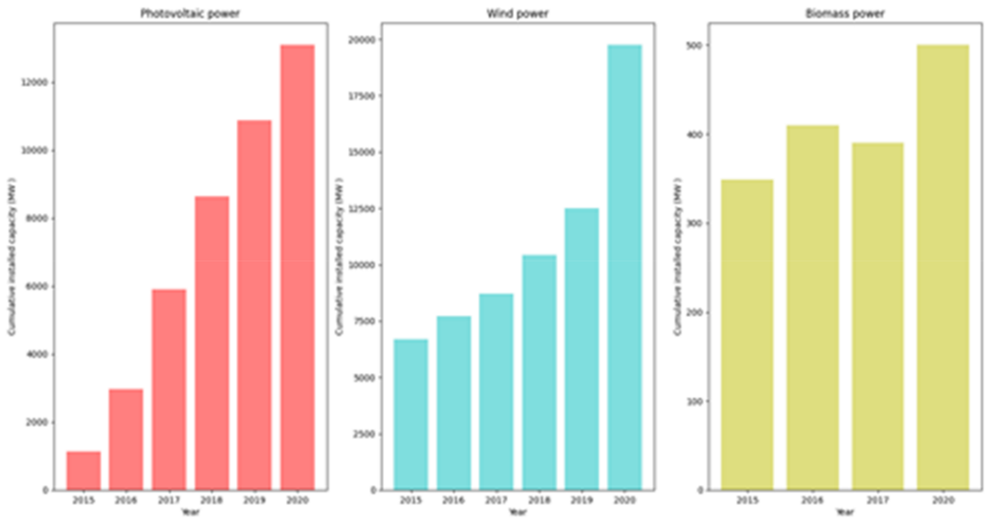

Figure 3. The cumulative installed capacity of photovoltaic power, wind power, and biomass power in Shanxi Province from 2015 to 2020.

5.1. Decision-Making Process

5.1.1. Determination of Alternatives and Criteria

To initiate the decision-making process, energy storage technologies were first selected. In this paper, we assumed that the selected alternative technologies are: PHS (A1), CAES (A2), FES (A3), lead–acid (A4), Li-ion (A5), hydrogen (A6), supercapacitors (A7), SMES (A8), and thermochemical storage (A9). Based on a previous study [7,18,22,34], the criteria that needed to be considered were determined, including energy efficiency (C1), response time (C2), lifetime (C3), energy density (C4), self-discharge losses (C5), power capital cost (C6), energy capital cost (C7), environmental dimension (C8), and social acceptance (C9). The characteristics of each criterion of the alternative technologies are shown in Table 2 in Section 3. In addition, we invited ten experts to provide their opinions on energy storage technology selection. These experts were from China University of Mining and Technology (Beijing), North China Electric Power University, Shanxi International Energy Company, and other units. Experts in the corresponding research fields have rich experience and knowledge in energy storage. Hence, their evaluation is considered reliable.

5.1.2. Evaluation of Storage Requirements

In the approach proposed in this study, experts provided storage requirements information associated with the development of renewable energy for the given use case. Assuming that the specific requirement information is shown in Table 4, then the initial target matrix can be constructed according to the requirement information.

Table 4. Demand evaluation information of experts.

Experts	Energy Efficiency (%)	Response Time	Lifetime (Years)	Energy Density (Wh/kg)	Self-Discharge Losses (%/day)	Power Capital Cost (USD/kw)	Energy Capital Cost (USD/kwh)	Environmental Dimension	Social Acceptance
1	(50, 80)	Short	(10, 30)	(40, 70)	(1, 8)	(100, 1000)	(50, 300)	Low	High
2	(55, 75)	Very short	(15, 25)	(10, 100)	(0.5, 8)	(300, 1000)	(200, 450)	Very low	High
3	(48, 80)	Very short	(12, 30)	(20, 80)	(0.5, 10)	(200, 500)	(600, 5000)	Very low	Very high
4	(60, 80)	Medium	(15, 30)	(15, 50)	(0.1, 5)	(150, 500)	(150, 500)	Low	High
5	(70, 80)	Medium	(10, 40)	(25, 120)	(0.5, 15)	(50, 300)	(300, 450)	Low	Medium
6	(40, 85)	Short	(20, 50)	(20, 50)	(0.1, 30)	(200, 400)	(200, 1000)	Low	High
7	(50, 95)	Short	(15, 50)	(12, 80)	(0.1, 15)	(200, 500)	(1000, 10,000)	Very low	High
8	(60, 90)	Medium	(10, 35)	(40, 80)	(9, 18)	(600, 1000)	(150, 800)	Medium	Medium
9	(35, 75)	Very short	(5, 20)	(35, 80)	(0.5, 11)	(400, 600)	(350, 600)	Medium	High
10	(65, 80)	Short	(10, 30)	(45, 60)	(25, 55)	(80, 500)	(200, 800)	Very low	Very high

5.1.3. Data Transformation and Fusion

The initial decision matrices could be obtained based on the approach in Section 4. However, the characteristics of each criterion of energy storage technologies are not only a definite value; for example, the PHS's energy efficiency may be 65–75 [37] or 75–80 [38], meaning the numbers in this interval are likely to be taken and all of them were likely to be selected as the basic data when experts constructed the initial matrices for decision making. Hence, there could have been many situations in the initial decision matrices, and every expert needed to determine the decision's basic data value of the characteristics of each criterion on the basis of data in Table 2. Subsequently, we transformed the data into fuzzy numbers and added a probability evaluation following the rules in Section 4; thus, the initial decision matrices could finally be obtained. The decision basic data and initial decision matrix of Expert 1 are shown in Tables 5 and 6, and the other experts' decision basic data and matrices are given in Appendix A.

Table 5. Decision basic data of Expert 1.

Technologies	Energy Efficiency (%)	Response Time	Lifetime (Years)	Energy Density (Wh/kg)	Self-Discharge Losses (%/day)	Power Capital Cost (USD/kw)	Energy Capital Cost (USD/kwh)	Environmental Dimension	Social Acceptance
PHS	(65, 75)	Medium	(30, 60)	(0.5, 1.5)	(0.0001, 0.0001)	(600, 2000)	(5, 100)	Very high	Very high
CAES	(41, 75)	Long	(20, 40)	(30, 60)	(0.0001, 0.0001)	(400, 800)	(50, 150)	Very high	Very high
FES	(80, 90)	Medium	(15, 20)	(10, 30)	(20,100)	(250, 350)	(1000, 5000)	Very high	Very high
Lead–Acid	(75, 80)	Very short	(3, 12)	(30, 50)	(0.1,0.3)	(300, 600)	(150, 500)	Very high	Medium
Li-ion	(65, 75)	Very short	(5, 15)	(75, 250)	(0.1, 0.3)	(1200, 4000)	(600, 2500)	Low	High
Hydrogen	(35, 40)	Medium	(5, 15)	(800, 1000)	(0.5, 2)	(500, 10,000)	(2, 15)	High	Medium
Super-capacitors	(85, 98)	Short	(10, 20)	(0.1, 15)	(20, 40)	(100, 300)	(300, 2000)	Low	Medium
SMES	(90, 95)	Short	(20, 30)	(0.5, 5)	(10, 15)	(200, 300)	(1000, 10,000)	Very high	Medium
Thermal (TES)	(14, 18)	Long	(5, 15)	(30, 60)	(0.05, 1)	(100, 400)	(3, 130)	Low	Medium

Table 6. Initial decision matrix of Expert 1.

<table>
<tr><th>Technologies</th><th>Energy Efficiency (%)</th><th>Response Time</th><th>Lifetime (Years)</th><th>Energy Density (Wh/kg)</th><th>Self-Discharge Losses (%/Day)</th><th>Power Capital Cost (USD/kw)</th><th>Energy Capital Cost (USD/kwh)</th><th>Environmental Dimension</th><th>Social Acceptance</th></tr>
<tr><td>PHS</td><td>(0.2157 | 0.6500, 0.7511 | 0.3500)</td><td>(0.5000 | 0.4400, 0.4500 | 0.5600)</td><td>(0.3026 | 0.8100, 0.3948 | 0.1900)</td><td>(0.0004 | 0.9000, 0.9989 | 0.1000)</td><td>(0.0000 | 0.7600, 1.0000 | 0.2400)</td><td>(0.0539 | 0.3900, 0.8203 | 0.6100)</td><td>(0.0004 | 0.7000, 0.9915 | 0.3000)</td><td>(0.9000 | 0.8820, 0.1000 | 0.1180)</td><td>(0.9000 | 0.4300, 0.1000 | 0.5700)</td></tr>
<tr><td>CAES</td><td>(0.1360 | 0.5000, 0.7511 | 0.5000)</td><td>(0.7500 | 0.5140, 0.2000 | 0.4860)</td><td>(0.2017 | 0.5300, 0.5965 | 0.4700)</td><td>(0.0229 | 0.4670, 0.9543 | 0.5330)</td><td>(0.0000 | 0.4600, 1.0000 | 0.5400)</td><td>(0.0359 | 0.7800, 0.9281 | 0.2200)</td><td>(0.0043 | 0.5320, 0.9872 | 0.4680)</td><td>(0.9000 | 0.3050, 0.1000 | 0.6950)</td><td>(0.9000 | 0.6250, 0.1000 | 0.3750)</td></tr>
<tr><td>FES</td><td>(0.2655 | 0.4930, 0.7014 | 0.5070)</td><td>(0.5000 | 0.8400, 0.4500 | 0.1600)</td><td>(0.1513 | 0.5490, 0.7983 | 0.4510)</td><td>(0.0076 | 0.7700, 0.9771 | 0.2300)</td><td>(0.1773 | 0.2360, 0.1137 | 0.7640)</td><td>(0.0225 | 0.4500, 0.9686 | 0.5500)</td><td>(0.0851 | 0.6930, 0.5744 | 0.3070)</td><td>(0.9000 | 0.4400, 0.1000 | 0.5600)</td><td>(0.9000 | 0.5420, 0.1000 | 0.4580)</td></tr>
<tr><td>Lead–acid</td><td>(0.2489 | 0.8000, 0.7346 | 0.2000)</td><td>(0.1000 | 0.7810, 0.9000 | 0.2190)</td><td>(0.0303 | 0.7570, 0.8790 | 0.2430)</td><td>(0.0229 | 0.7110, 0.9619 | 0.2890)</td><td>(0.0009 | 0.7000, 0.9973 | 0.3000)</td><td>(0.0270 | 0.4900, 0.9461 | 0.5100)</td><td>(0.0128 | 0.2390, 0.9574 | 0.7610)</td><td>(0.9000 | 0.2000, 0.1000 | 0.8000)</td><td>(0.5000 | 0.4670, 0.4500 | 0.5330)</td></tr>
<tr><td>Li-ion</td><td>(0.2157 | 0.3200, 0.7511 | 0.6800)</td><td>(0.1000 | 0.5920, 0.9000 | 0.4080)</td><td>(0.0504 | 0.6100, 0.8487 | 0.3900)</td><td>(0.0572 | 0.2400, 0.8095 | 0.7600)</td><td>(0.0009 | 0.4880, 0.9973 | 0.5120)</td><td>(0.1078 | 0.2700, 0.6406 | 0.7300)</td><td>(0.0511 | 0.6000, 0.7872 | 0.4000)</td><td>(0.3500 | 0.5600, 0.6000 | 0.4400)</td><td>(0.7500 | 0.6700, 0.2000 | 0.3300)</td></tr>
<tr><td>Hydrogen</td><td>(0.1161 | 0.4800, 0.8673 | 0.5200)</td><td>(0.5000 | 0.3360, 0.4500 | 0.6640)</td><td>(0.0504 | 0.3900, 0.8487 | 0.6100)</td><td>(0.6097 | 0.3800, 0.2379 | 0.6200)</td><td>(0.0044 | 0.3300, 0.9823 | 0.6700)</td><td>(0.0449 | 0.7200, 0.1016 | 0.2800)</td><td>(0.0002 | 0.5490, 0.9987 | 0.4510)</td><td>(0.7500 | 0.5490, 0.2000 | 0.4510)</td><td>(0.5000 | 0.8700, 0.4500 | 0.1300)</td></tr>
<tr><td>Super-capacitors</td><td>(0.2820 | 0.6600, 0.6748 | 0.3400)</td><td>(0.3500 | 0.2700, 0.6000 | 0.7300)</td><td>(0.1009 | 0.4830, 0.7983 | 0.5170)</td><td>(0.0001 | 0.7400, 0.9999 | 0.2600)</td><td>(0.1773 | 0.5550, 0.6455 | 0.4450)</td><td>(0.0090 | 0.3380, 0.9731 | 0.6620)</td><td>(0.0255 | 0.6820, 0.8298 | 0.3180)</td><td>(0.3500 | 0.8300, 0.6000 | 0.1700)</td><td>(0.5000 | 0.5400, 0.4500 | 0.4600)</td></tr>
<tr><td>SMES</td><td>(0.2986 | 0.7250, 0.6848 | 0.2750)</td><td>(0.3500 | 0.1900, 0.6000 | 0.8100)</td><td>(0.2017 | 0.2160, 0.6974 | 0.7840)</td><td>(0.0004 | 0.5510, 0.9962 | 0.4490)</td><td>(0.0886 | 0.4900, 0.8671 | 0.5100)</td><td>(0.0180 | 0.8600, 0.9731 | 0.1400)</td><td>(0.0851 | 0.5850, 0.1488 | 0.4150)</td><td>(0.9000 | 0.8590, 0.1000 | 0.1410)</td><td>(0.5000 | 0.7340, 0.4500 | 0.2660)</td></tr>
<tr><td>Thermal (TES)</td><td>(0.0465 | 0.2900, 0.9403 | 0.7100)</td><td>(0.7500 | 0.4180, 0.2000 | 0.5820)</td><td>(0.0504 | 0.1500, 0.8487 | 0.8500)</td><td>(0.0229 | 0.4590, 0.9543 | 0.5410)</td><td>(0.0004 | 0.3100, 0.9911 | 0.6900)</td><td>(0.0090 | 0.2590, 0.9641 | 0.7410)</td><td>(0.0003 | 0.7900, 0.9889 | 0.2100)</td><td>(0.3500 | 0.4300, 0.6000 | 0.5700)</td><td>(0.5000 | 0.3700, 0.4500 | 0.6300)</td></tr>
</table>

In addition, based on the method of transformation and fusion in Section 4, the initial energy requirement information in Table 4 could be transformed into a PDHFS, and the target matrix is shown as follows:

$$Dm = \begin{bmatrix}
(0.1605|0.5500, 0.7432|0.4500) & (0.3500|0.3500, 0.6000|0.6500) & (0.0847|0.6500, 0.8306|0.3500) & (0.1458|0.5700, 0.7630|0.4300) & (0.0221|0.4500, 0.7574|0.5500) & (0.0645|0.6000, 0.8066|0.4000) & (0.0430|0.8500, 0.9283|0.1500) & (0.3500|0.5000, 0.6000|0.5000) & (0.7500|0.2000, 0.2000|0.8000) \\
(0.1765|0.6500, 0.7593|0.3500) & (0.1000|0.8000, 0.9000|0.2000) & (0.1411|0.6400, 0.7742|0.3600) & (0.0729|0.6500, 0.7995|0.3500) & (0.0044|0.5500, 0.6031|0.4500) & (0.0322|0.7500, 0.4198|0.2500) & (0.0144|0.5000, 0.9319|0.5000) & (0.1000|0.5600, 0.9000|0.4400) & (0.7500|0.5500, 0.2000|0.4500) \\
(0.1541|0.6300, 0.7432|0.3700) & (0.1000|0.3500, 0.9000|0.6500) & (0.1411|0.3500, 0.8306|0.6500) & (0.2005|0.5500, 0.7083|0.4400) & (0.0022|0.2500, 0.7133|0.7500) & (0.0645|0.5500, 0.6777|0.4500) & (0.0430|0.4000, 0.9139|0.6000) & (0.1000|0.4600, 0.9000|0.5400) & (0.9000|0.4000, 0.1000|0.6000) \\
(0.2186|0.4500, 0.7501|0.5500) & (0.5000|0.5500, 0.4500|0.4500) & (0.1129|0.5500, 0.7742|0.4500) & (0.0547|0.4500, 0.7083|0.5500) & (0.0022|0.5000, 0.69127|0.5000) & (0.0484|0.6000, 0.7099|0.4000) & (0.0359|0.5400, 0.7848|0.4600) & (0.3500|0.5300, 0.6000|0.4700) & (0.7500|0.7500, 0.2000|0.2500) \\
(0.2030|0.6400, 0.6877|0.3600) & (0.5000|0.7500, 0.4500|0.2500) & (0.1694|0.7500, 0.7177|0.2500) & (0.1094|0.3500, 0.6354|0.6500) & (0.0110|0.5000, 0.7574|0.5000) & (0.0322|0.3500, 0.8388|0.6500) & (0.0215|0.3000, 0.7131|0.7000) & (0.3500|0.7500, 0.6000|0.3500) & (0.5000|0.7000, 0.4500|0.3000) \\
(0.2030|0.8000, 0.7033|0.2000) & (0.3500|0.5000, 0.6000|0.5000) & (0.2258|0.3500, 0.6613|0.6500) & (0.1641|0.7500, 0.7812|0.2500) & (0.0221|0.6500, 0.6427|0.3500) & (0.0645|0.3600, 0.7421|0.6400) & (0.0072|0.7500, 0.6414|0.2500) & (0.3500|0.8000, 0.6000|0.2000) & (0.7500|0.5500, 0.2000|0.4500) \\
(0.2343|0.4500, 0.7501|0.5500) & (0.3500|0.3400, 0.6000|0.6600) & (0.2258|0.5700, 0.4354|0.4300) & (0.1276|0.6500, 0.7448|0.3500) & (0.0044|0.5500, 0.6251|0.4500) & (0.0484|0.8000, 0.7905|0.2000) & (0.0574|0.4700, 0.2827|0.5300) & (0.1000|0.6500, 0.9000|0.3500) & (0.7500|0.8000, 0.2000|0.2000) \\
(0.2186|0.8000, 0.7564|0.2000) & (0.5000|0.6800, 0.4500|0.3200) & (0.1411|0.5800, 0.8024|0.4200) & (0.1458|0.7500, 0.6901|0.2500) & (0.0441|0.6000, 0.6692|0.4000) & (0.0645|0.6500, 0.7421|0.3500) & (0.0359|0.8000, 0.5696|0.2000) & (0.5000|0.5000, 0.4500|0.5000) & (0.5000|0.3500, 0.4500|0.6500) \\
(0.1874|0.4000, 0.7501|0.6000) & (0.1000|0.4600, 0.9000|0.5500) & (0.0847|0.4500, 0.8024|0.5500) & (0.1641|0.8600, 0.7488|0.1400) & (0.0004|0.8000, 0.7354|0.2000) & (0.1289|0.3300, 0.6132|0.6700) & (0.0251|0.2600, 0.9139|0.7400) & (0.5000|0.7500, 0.4500|0.2500) & (0.7500|0.4700, 0.2000|0.5300) \\
(0.2186|0.7000, 0.7189|0.3000) & (0.3500|0.3500, 0.6000|0.6500) & (0.0565|0.6000, 0.8306|0.4000) & (0.1823|0.4500, 0.6536|0.5500) & (0.0662|0.9000, 0.6913|0.1000) & (0.0387|0.5500, 0.7905|0.4500) & (0.0359|0.3000, 0.9211|0.7000) & (0.1000|0.8000, 0.9000|0.2000) & (0.9000|0.4200, 0.1000|0.5800)
\end{bmatrix}$$

Therefore, the initial decision matrices and initial target matrix were obtained through the above transformation.

5.1.4. Weight Calculation

The calculation of the criteria weight comprises three steps. First, calculate the average value of the criteria based on the Equation (9). The average value matrices for each expert were obtained and detailed in Appendix B. Second, calculate the entropy of each criterion based on Equation (10), and the entropy can be used in the third step of the weight calculation based on Equation (11). The criteria weights could be calculated based on each expert's decision matrix as shown in Table 7. After obtaining the criteria weights of Expert 1 to Expert 10, we calculated the final weight vector of criteria by averaging ten criteria weights, with the final weight vector of criteria being: $W = \{0.0994, 0.1047, 0.1024, 0.1022, 0.1178, 0.1416, 0.1535, 0.0940, 0.0844\}$.

Table 7. Weights of the evaluation criteria.

Criteria	Energy Efficiency	Response Time	Lifetime	Energy Density	Discharge Duration	Power Capital Cost	Energy Capital Cost	Environmental Dimension	Social Acceptance
Expert 1	0.1224	0.1683	0.0855	0.1276	0.0651	0.1425	0.1109	0.0888	0.0889
Expert 2	0.1152	0.0908	0.1654	0.0499	0.1022	0.0863	0.1782	0.1264	0.0855
Expert 3	0.0490	0.1260	0.0993	0.0999	0.1824	0.1238	0.1795	0.0692	0.0710
Expert 4	0.0864	0.0886	0.0780	0.1826	0.0972	0.1505	0.1309	0.0929	0.0929
Expert 5	0.0839	0.0778	0.1519	0.1239	0.0912	0.0964	0.1942	0.0628	0.1178
Expert 6	0.0999	0.0844	0.0810	0.1061	0.1625	0.2058	0.1075	0.0965	0.0563
Expert 7	0.1276	0.0844	0.0947	0.0596	0.1234	0.1622	0.1738	0.1113	0.0628
Expert 8	0.0405	0.1732	0.1463	0.0683	0.1287	0.0869	0.1404	0.1139	0.1017
Expert 9	0.2086	0.0732	0.0411	0.1148	0.1326	0.1132	0.1295	0.1078	0.0792
Expert 10	0.0604	0.0803	0.0811	0.0896	0.0921	0.2481	0.1902	0.0702	0.0880
Final weight	0.0994	0.1047	0.1024	0.1022	0.1178	0.1416	0.1535	0.0940	0.0844

Based on the initial target matrix, the weights of the experts could be calculated using the maximizing deviation measurement and Euclidean distance in Equation (13). The calculation result of the expert weight vector was $\eta = \{0.1055, 0.0964, 0.0980, 0.1076, 0.0985, 0.0924, 0.1011, 0.0971, 0.1056, 0.0976\}$.

5.1.5. Distance Measurement and Energy Storage Technology Selection

Distance measurement should use a weighted matrix, and the initial decision matrix and initial target matrix need to be weighted first using the weighted averaging operator. The weighted decision matrix and target matrix are shown in Appendix C. To that end, we can calculate the distance between decision matrix and the target matrix. The distance between the decision matrix and target matrix can be obtained based on the calculation following Equation (4). The value of distance and the ranking results are shown in Figure 4. We can see in Figure 4 that the results for nine different storage technologies are different. The smaller the distance value, the closer the storage is to the target, and the better it can meet the requirements set. Therefore, when choosing the energy storage technology, we ranked distance values from the lowest to the highest, and the ranking results are shown in Figure 4. The distances from low to high were ranked as A6 > A2 > A1 > A7 > A3 > A5 > A4 > A9 > A8. This shows that according to the views of experts, hydrogen is the most suitable energy storage technology based on the requirements set for renewable energy storage.

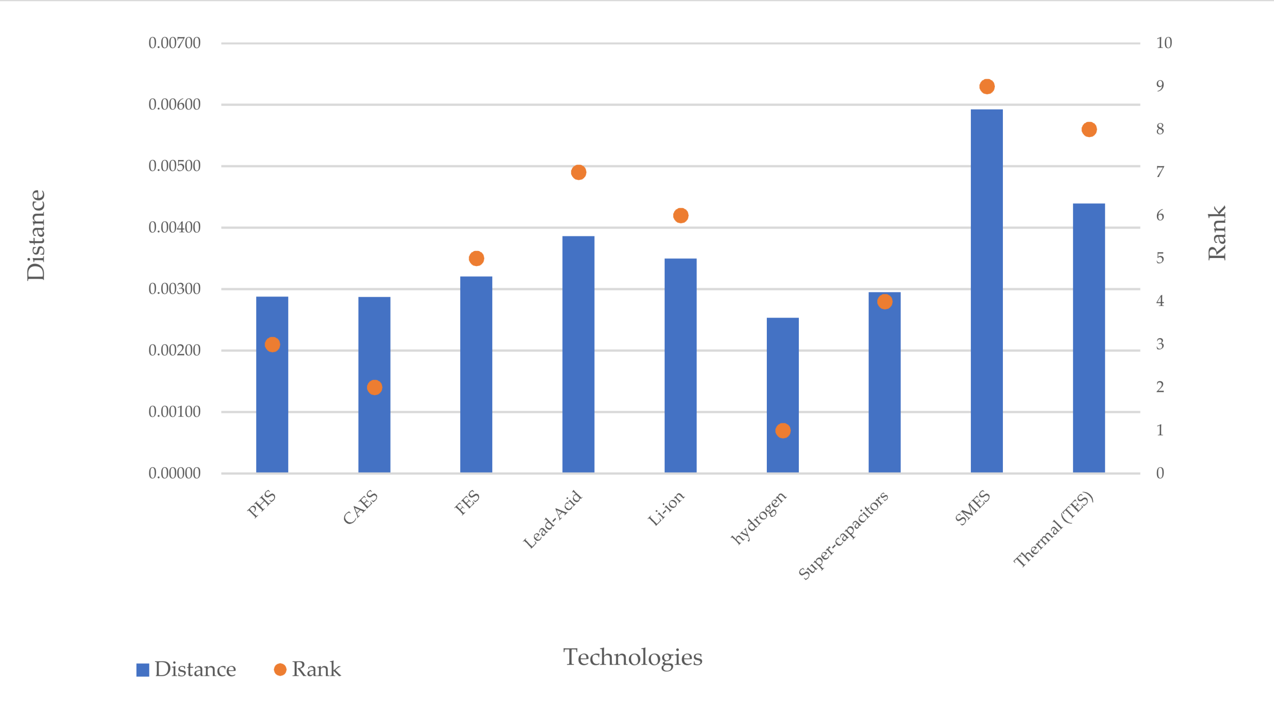

Figure 4. Distance calculation and ranking results.

5.2. Sensitivity Analysis

A sensitivity analysis was conducted to show the application of the approach in different scenarios. Suitable energy storage technologies for energy storage requirements may be different when the storage requirements of new energy and renewable energy are different. Thus, three scenarios are given to illustrate the different requirements of different energy storage projects. In each scenario, every expert gives the requirement information of each criterion, and the information in Scenarios 1 to 3 are shown in Appendix D.

Using the calculation of the model proposed herein, the results in each scenario can be obtained. The distance calculation result and ranking result in Scenario 1 are shown in Figure 5. It is indicated that in Scenario 1, the distances from low to high are ranked as: A2 > A6 > A3 > A5 > A1 > A4 > A7 > A9 > A8. In this scenario, the most suitable technology is compressed air energy storage. Regarding Scenario 2, the distance calculation result and ranking result are shown in Figure 6. According to the distance value and ranking of Figure 6., we can see that the ranking of storage technologies is A6 > A2 > A1 > A3 > A7 > A5 > A4 > A9 > A8. In this scenario, the most suitable energy storage technology is hydrogen. Finally, in Scenario 3, the distance ranking is A2 > A6 > A1 > A3 > A5 > A7 > A4 > A9 > A8, as shown in Figure 7, and the optimal energy storage technology is compressed air energy storage.

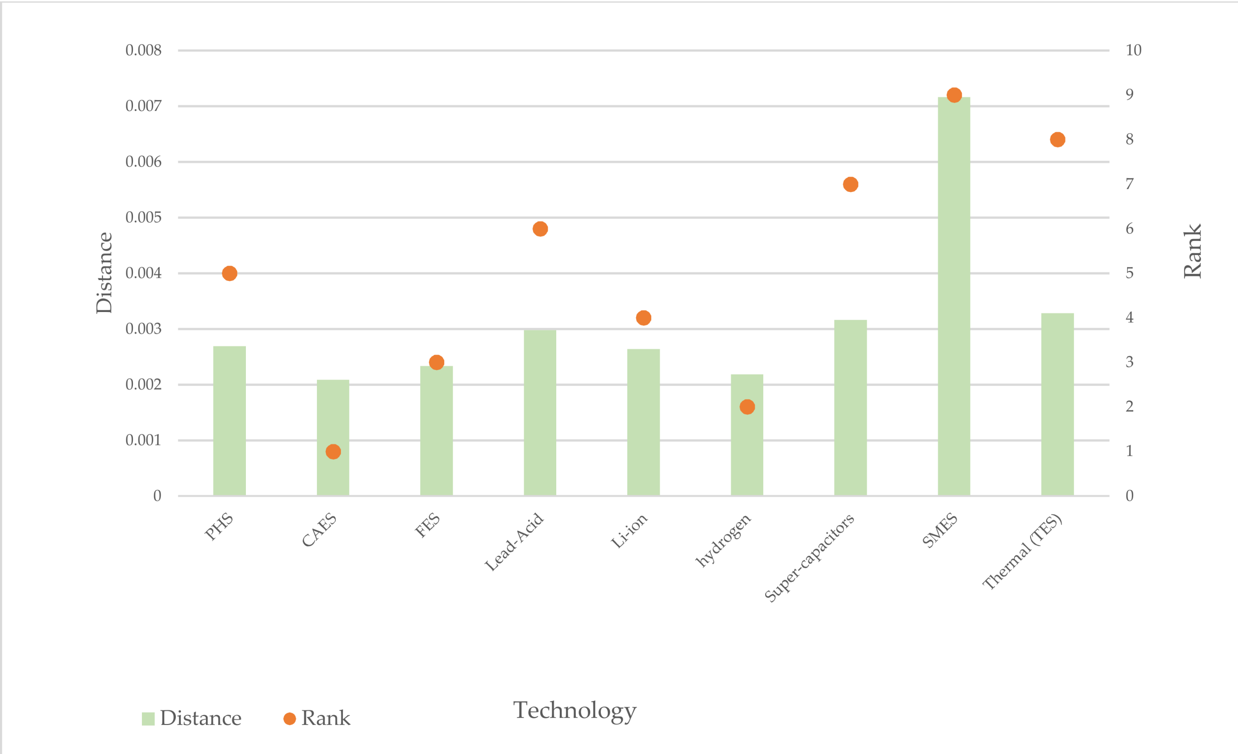

Figure 5. The distance calculation and ranking results in Scenario 1.

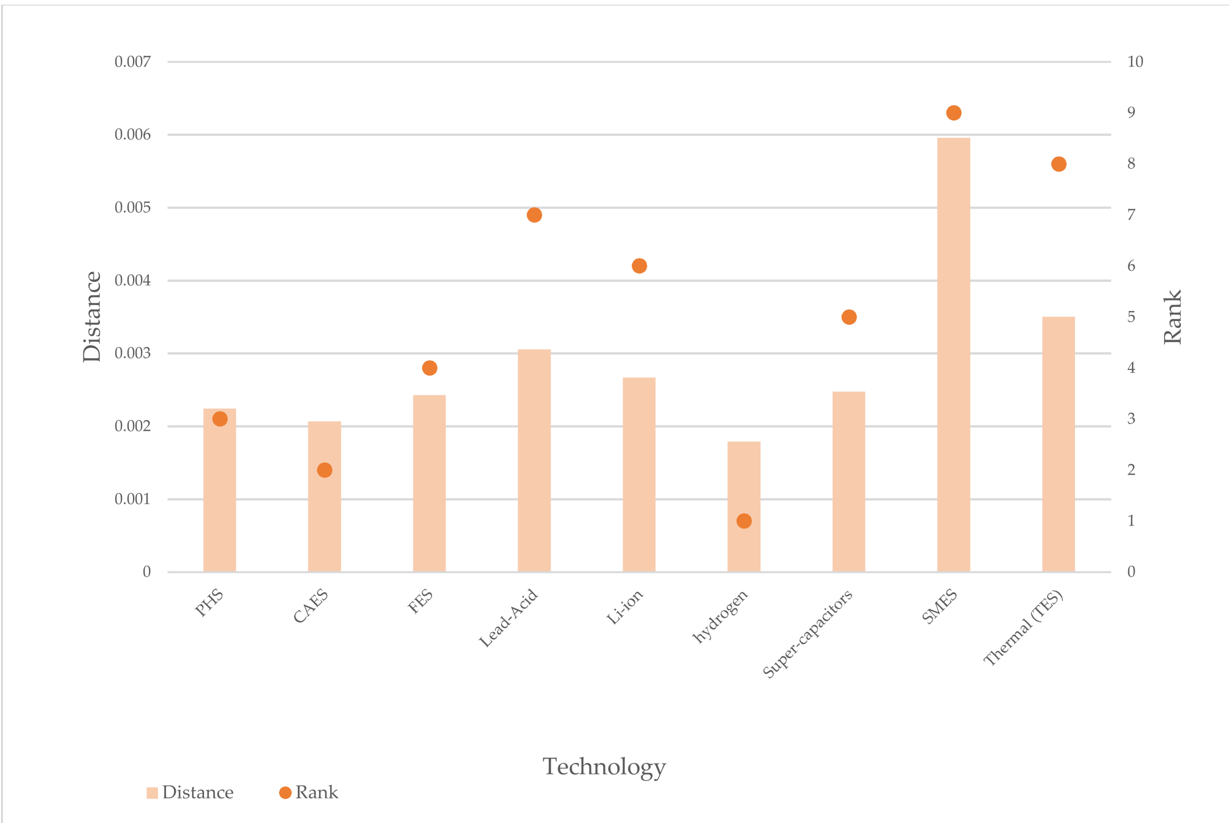

Figure 6. The distance calculation and ranking results in Scenario 2.

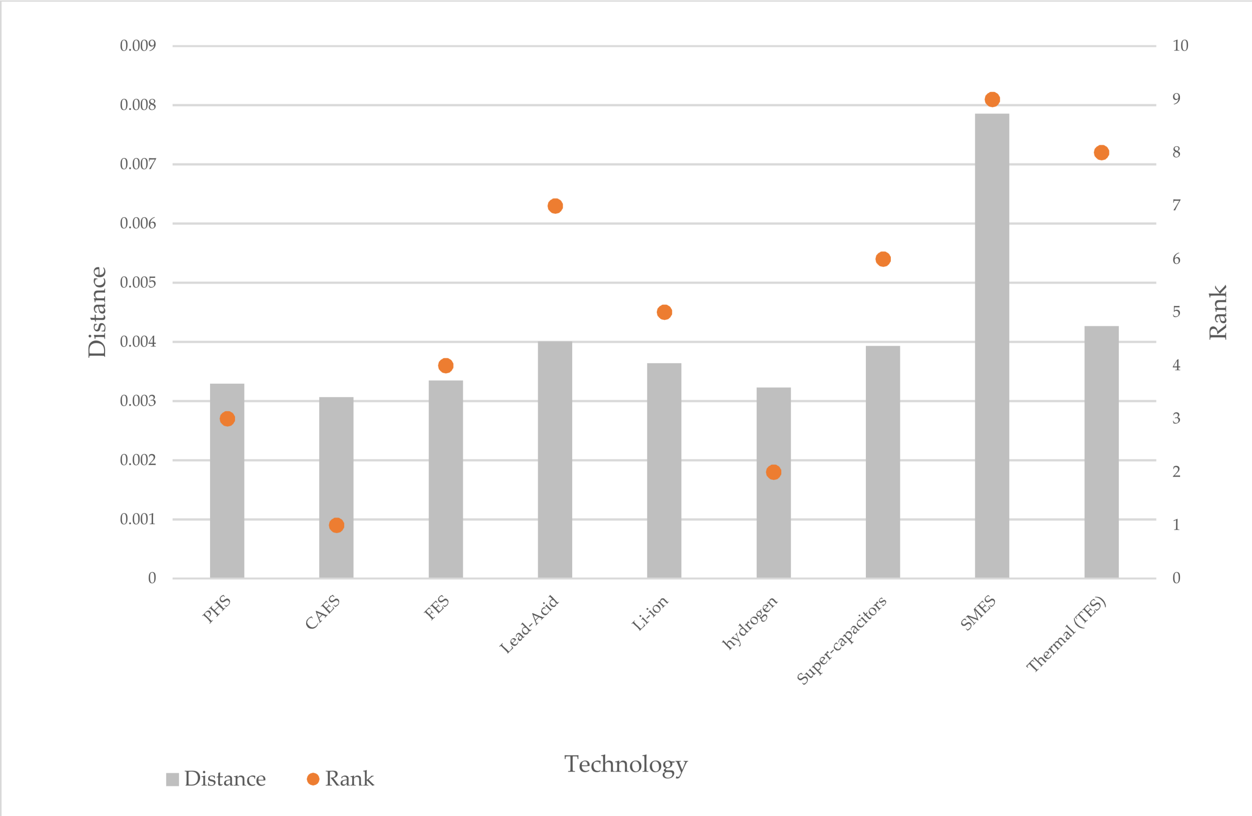

Figure 7. The distance calculation and ranking results in Scenario 3.

5.3. Discussion

The results obtained indicate that in different requirement scenarios, the most suitable storage technology selection is different (shown in Figure 8); for example, in Scenario 2, the optimal energy storage technology is hydrogen, whereas in Scenario 1 and Scenario 3, compressed air is the most suitable energy storage technology. Compared to the existing reference, Zhang et al. [18] used the intuitionistic fuzzy MULTI-MOORA approach for energy storage technology selection and ranked all technologies separately based on technology, economy, and environment, and then integrated the ranks of all aspects to obtain comprehensive sorting, finally obtaining the best and worst energy storage technology. L. Li et al. proposed a multi-objective optimization approach to obtain optimal energy storage alternatives for applications [18], while Y. Liu and Du [16], Ren and Ren [28], and Çolak and Kaya [29] ranked energy storage technologies and obtained an optimal energy storage technology using MCDM methods. The above references only use a variety of different methods to rank energy storage technologies, not capturing storage requirements and relevant application scenarios. Albawab et al. [31] conducted a sensitivity analysis and obtained different ranking results under different scenarios. However, the reference only changes the weights of the criteria and does not consider the requirements. As shown in the sensitivity analysis, the energy storage technologies selected in different storage requirement scenarios are different, and energy storage requirements affect the choice of energy storage technology. This also means that the energy storage technology selection should be based on actual needs and requirements and that the energy storage technology selection model proposed herein has practical significance.

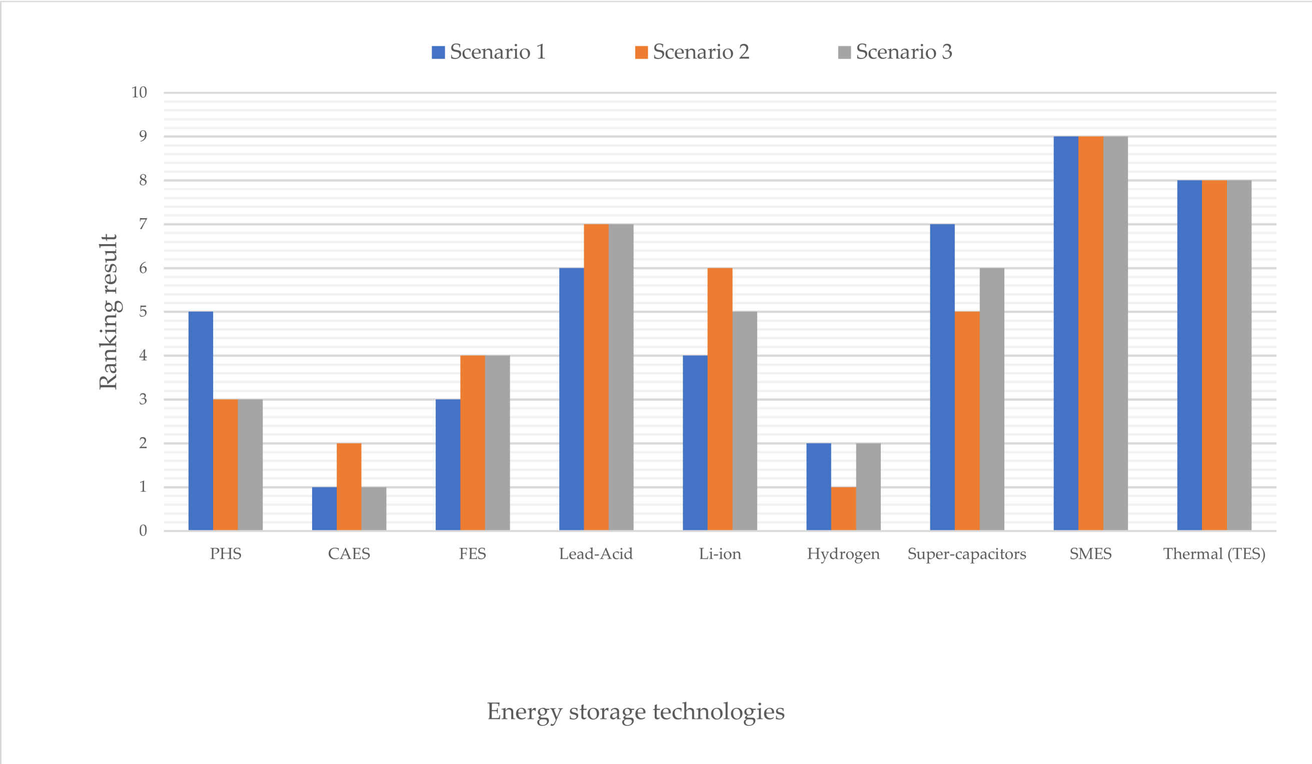

Figure 8. The ranking results in Scenario 1, Scenario 2, and Scenario 3.

6. Conclusions

This study develops a method for selecting suitable energy storage technology based on energy storage requirements. In this work, we regard energy storage technology selection as an MCDM problem and construct a transformation and fusion method to express the information in a PDHFS. Next, the entropy weight method and maximizing deviation measurement are used to calculate the weights of the criteria and experts, respectively. Based on this distance measurement, a suitable energy storage technology can be selected. Finally, the developed framework is applied, using the Shanxi Province in China as a case study in the phase of energy transition to an energy mix with high shares of renewables. The strengths of this study are: (1) the method for data transformation and fusion contains probability information transformation, in that the expert can give the probability evaluation for each criterion. The background of energy storage technology selection is complex, and some characteristics cannot be expressed in certain data. Consequently, a PDHFS is required to describe uncertain information. (2) The framework for energy storage technology selection proposed herein considers the energy storage requirements and can thus be applied to actual renewable energy storage projects, capturing not only technology, but also economic, social, and environmental criteria.

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Nomenclature

Nomenclature		*Tm*	**The Target Matrix**
Variable			
Du	Dual hesitant fuzzy sets	*Parameter*	
PD, M_A, N_A, M_B,N_B	Probability dual hesitant fuzzy set	γ^+	Maximum values in $\widetilde{hp}(x)$
pd	Probability dual hesitant fuzzy number	φ^+	Maximum values in $\widetilde{gp}(x)$
W	The weight of PDHFNs	p^h	Probabilities of γ
PDHFW	The weighted PDHFNs	p^g	Probabilities of φ
(a_{ij}^L, a_{ij}^U)	The lower bound and upper bound of the Interval number a_{ij}	λ	Parameter in distance function, usually assumed as 2.
d(A,B)	Distance between PDHFS A and B	z	The number of experts
$(\overline{a}_{ij}^L, \overline{a}_{ij}^U)$	Normalized value of (a_{ij}^L, a_{ij}^U)		
α_{ij}	Fuzzy number	*Abbreviation*	
h_{ij}	Membership degree of fuzzy number α_{ij}	MCDM	Multi-criteria decision-making
g_{ij}	Non-membership degree of fuzzy number α_{ij}	PHS	Pumped hydro storage
$\widetilde{hp}(x)$	Membership degree function of PDHFS *PD*	HFS	Hesitant fuzzy set
$\widetilde{gp}(x)$	Non-membership function of PDHFS *PD*	CAES	Compressed air energy storage
$\gamma \vert p^h$	Elements in $\widetilde{hp}(x)$	FES	Flywheel energy storage
$\varphi \vert p^g$	Elements in $\widetilde{gp}(x)$	Li-ion	lithium-ion
$D(pd_1, pd_2)$	Euclidean distance	SMES	Superconducting magnetic energy storage
η	The expert weight vector	DHFS	Dual hesitant fuzzy set
A	The set of energy storage technologies	PDHFS	Probability dual hesitant fuzzy set
C	The set of criteria	PDHFN	Probability dual hesitant fuzzy number

Appendix A

The decision basic data and initial decision matric of experts are shown in Tables A1–A18 in Appendix A.

Table A1. Decision basic data of Expert 2.

Technologies	Energy Efficiency (%)	Response Time	Lifetime (Years)	Energy Density (Wh/kg)	Self-Discharge Losses (%/day)	Power Capital Cost (USD/kw)	Energy Capital Cost (USD/kwh)	Environmental Dimension	Social Acceptance
PHS	(65, 80)	Medium	(30, 60)	(0.5, 1.5)	(0.0001, 0.0001)	(600, 4600)	(5, 430)	Very high	Very high
CAES	(41, 75)	Long	(20, 40)	(30, 60)	(0.0001, 0.0001)	(400, 800)	(50, 150)	Very high	Very high
FES	(80, 85)	Medium	(15, 20)	(10, 30)	(20, 100)	(250, 350)	(1000, 5000)	Very high	Very high
Lead–acid	(75, 80)	Very short	(3, 12)	(30, 50)	(0.1, 0.3)	(300, 600)	(150, 500)	Very high	Medium
Li-ion	(65, 78)	Very short	(5, 15)	(75, 250)	(0.1, 0.3)	(1200, 4000)	(600, 2500)	Low	High
Hydrogen	(35, 40)	Medium	(5, 20)	(800, 1000)	(0.5, 2)	(500, 10,000)	(2, 15)	High	Medium
Super-capacitors	(85, 98)	Short	(10, 20)	(0.1, 15)	(20, 40)	(100, 300)	(300, 2000)	Low	Medium
SMES	(90, 95)	Short	(20, 30)	(0.5, 5)	(10, 15)	(200, 300)	(1000, 10,000)	Very high	Medium
Thermal (TES)	(14, 18)	Long	(5, 15)	(30, 60)	(0.05, 1)	(100, 400)	(3, 130)	Low	Medium

Table A2. Initial decision matrix of Expert 2.

Technologies	Energy Efficiency (%)	Response Time	Lifetime (Years)	Energy Density (Wh/kg)	Self-Discharge Losses (%/Day)	Power Capital Cost (USD/kw)	Energy Capital Cost (USD/kwh)	Environmental Dimension	Social Acceptance
PHS	(0.2153 ∣ 0.7520, 0.7315 ∣ 0.2480)	(0.5000 ∣ 0.6400, 0.4500 ∣ 0.3600)	(0.3000 ∣ 0.6000, 0.4001 ∣ 0.4000)	(0.0004 ∣ 0.6200, 0.9989 ∣ 0.3800)	(0.0000 ∣ 0.3600, 1.0000 ∣ 0.6400)	(0.0505 ∣ 0.7600, 0.6127 ∣ 0.2400)	(0.0004 ∣ 0.6000, 0.9634 ∣ 0.4000)	(0.9000 ∣ 0.4570, 0.1000 ∣ 0.5430)	(0.9000 ∣ 0.6580, 0.1000 ∣ 0.3420)
CAES	(0.1358 ∣ 0.5400, 0.7516 ∣ 0.4600)	(0.7500 ∣ 0.7600, 0.2000 ∣ 0.2400)	(0.2000 ∣ 0.7600, 0.6001 ∣ 0.2400)	(0.0229 ∣ 0.6540, 0.9543 ∣ 0.3460)	(0.0000 ∣ 0.7400, 1.0000 ∣ 0.2600)	(0.0337 ∣ 0.8450, 0.9326 ∣ 0.1550)	(0.0043 ∣ 0.4200, 0.9872 ∣ 0.5800)	(0.9000 ∣ 0.7540, 0.1000 ∣ 0.2460)	(0.9000 ∣ 0.6250, 0.1000 ∣ 0.3750)
FES	(0.2649 ∣ 0.8560, 0.7185 ∣ 0.1440)	(0.5000 ∣ 0.5400, 0.4500 ∣ 0.4600)	(0.1500 ∣ 0.6200, 0.8000 ∣ 0.3800)	(0.0076 ∣ 0.5420, 0.9771 ∣ 0.4580)	(0.1773 ∣ 0.4340, 0.1137 ∣ 0.5660)	(0.0211 ∣ 0.6350, 0.9705 ∣ 0.3650)	(0.0851 ∣ 0.6430, 0.5747 ∣ 0.3570)	(0.9000 ∣ 0.7350, 0.1000 ∣ 0.6250)	(0.9000 ∣ 0.5460, 0.1000 ∣ 0.4540)
Lead–acid	(0.2484 ∣ 0.6200, 0.7351 ∣ 0.3800)	(0.1000 ∣ 0.6570, 0.9000 ∣ 0.3430)	(0.0300 ∣ 0.4340, 0.8800 ∣ 0.5660)	(0.0229 ∣ 0.2400, 0.9619 ∣ 0.7600)	(0.0009 ∣ 0.7530, 0.9973 ∣ 0.2470)	(0.0253 ∣ 0.7630, 0.9495 ∣ 0.2370)	(0.0128 ∣ 0.4260, 0.9575 ∣ 0.5740)	(0.9000 ∣ 0.5400, 0.1000 ∣ 0.4600)	(0.5000 ∣ 0.4670, 0.4500 ∣ 0.5330)
Li-ion	(0.2153 ∣ 0.7000, 0.7417 ∣ 0.3000)	(0.1000 ∣ 0.3760, 0.9000 ∣ 0.6240)	(0.0504 ∣ 0.5400, 0.8487 ∣ 0.4600)	(0.0572 ∣ 0.3500, 0.8095 ∣ 0.6500)	(0.0009 ∣ 0.3460, 0.9973 ∣ 0.6540)	(0.1010 ∣ 0.5640, 0.6632 ∣ 0.4360)	(0.0510 ∣ 0.6600, 0.7873 ∣ 0.3400)	(0.3500 ∣ 0.8600, 0.6000 ∣ 0.1400)	(0.7500 ∣ 0.6700, 0.2000 ∣ 0.3300)
Hydrogen	(0.1159 ∣ 0.7540, 0.8675 ∣ 0.2460)	(0.5000 ∣ 0.5600, 0.4500 ∣ 0.4400)	(0.0500 ∣ 0.4310, 0.8500 ∣ 0.5690)	(0.6097 ∣ 0.3700, 0.2379 ∣ 0.6300)	(0.0044 ∣ 0.7600, 0.9823 ∣ 0.2400)	(0.0421 ∣ 0.7630, 0.1580 ∣ 0.2370)	(0.0002 ∣ 0.6420, 0.9987 ∣ 0.3580)	(0.7500 ∣ 0.3560, 0.2000 ∣ 0.6440)	(0.5000 ∣ 0.6500, 0.4500 ∣ 0.3500)
Super-capacitors	(0.2815 ∣ 0.8700, 0.6755 ∣ 0.1300)	(0.3500 ∣ 0.4860, 0.6000 ∣ 0.5140)	(0.0500 ∣ 0.7640, 0.8000 ∣ 0.2360)	(0.0001 ∣ 0.6400, 0.9886 ∣ 0.3600)	(0.1773 ∣ 0.7300, 0.6455 ∣ 0.2700)	(0.0084 ∣ 0.4760, 0.9747 ∣ 0.5240)	(0.0255 ∣ 0.7600, 0.8299 ∣ 0.2400)	(0.3500 ∣ 0.8300, 0.6000 ∣ 0.1700)	(0.5000 ∣ 0.3700, 0.4500 ∣ 0.6300)
SMES	(0.2980 ∣ 0.2400, 0.6854 ∣ 0.7600)	(0.3500 ∣ 0.8000, 0.6000 ∣ 0.2000)	(0.2000 ∣ 0.4250, 0.7000 ∣ 0.5750)	(0.0004 ∣ 0.7400, 0.9962 ∣ 0.2600)	(0.0886 ∣ 0.8670, 0.8671 ∣ 0.1330)	(0.0168 ∣ 0.8600, 0.9747 ∣ 0.1400)	(0.0851 ∣ 0.4700, 0.1494 ∣ 0.5300)	(0.9000 ∣ 0.8590, 0.1000 ∣ 0.1410)	(0.5000 ∣ 0.7674, 0.4500 ∣ 0.2326)
Thermal (TES)	(0.0464 ∣ 0.4200, 0.9404 ∣ 0.5800)	(0.7500 ∣ 0.3000, 0.2000 ∣ 0.7000)	(0.0500 ∣ 0.6250, 0.8500 ∣ 0.3480)	(0.0229 ∣ 0.7360, 0.9543 ∣ 0.2640)	(0.0004 ∣ 0.4860, 0.9911 ∣ 0.5140)	(0.0084 ∣ 0.2590, 0.9663 ∣ 0.7410)	(0.0003 ∣ 0.5700, 0.9889 ∣ 0.4300)	(0.3500 ∣ 0.5300, 0.6000 ∣ 0.4700)	(0.5000 ∣ 0.6540, 0.4500 ∣ 0.3460)

Table A3. Decision basic data of Expert 3.

Technologies	Energy Efficiency (%)	Response Time	Lifetime (Years)	Energy Density (Wh/kg)	Self-Discharge Losses (%/Day)	Power Capital Cost (USD/kw)	Energy Capital Cost (USD/kwh)	Environmental Dimension	Social Acceptance
PHS	(70, 75)	Medium	(30, 60)	(0.5, 1.5)	(0.0001, 0.0001)	(700, 2000)	(5, 100)	Very high	Very high
CAES	(41, 75)	Long	(20, 40)	(30, 60)	(0.0001, 0.0001)	(400, 800)	(50, 150)	Very high	Very high
FES	(80, 90)	Medium	(15, 20)	(10, 30)	(20, 100)	(250, 350)	(1000, 5000)	Very high	Very high
Lead–acid	(75, 80)	Very short	(3, 12)	(30, 50)	(0.1, 0.3)	(300, 600)	(150, 500)	Very high	Medium
Li-ion	(65, 78)	Very short	(5, 15)	(75, 250)	(0.1, 0.3)	(1200, 4000)	(600, 2500)	Low	High
Hydrogen	(35, 40)	Medium	(5, 20)	(800, 1000)	(0.5, 2)	(500, 10,000)	(2, 15)	High	Medium
Super-capacitors	(85, 98)	Short	(10, 25)	(0.1, 15)	(20, 40)	(100, 300)	(300, 2000)	Low	Medium
SMES	(90, 95)	Short	(20, 30)	(0.5, 5)	(10, 15)	(200, 300)	(1000, 10,000)	Very high	Medium
Thermal (TES)	(14, 18)	Long	(5, 15)	(30, 60)	(0.05, 1)	(100, 400)	(3, 130)	Low	Medium

Table A4. Initial decision matrix of Expert 3.

Technologies	Energy Efficiency (%)	Response Time	Lifetime (Years)	Energy Density (Wh/kg)	Self-Discharge Losses (%/Day)	Power Capital Cost (USD/kw)	Energy Capital Cost (USD/kwh)	Environmental Dimension	Social Acceptance
PHS	(0.2308 ∣ 0.3760, 0.7527 ∣ 0.6240)	(0.5000 ∣ 0.3600, 0.4500 ∣ 0.6400)	(0.2966 ∣ 0.8100, 0.4067 ∣ 0.1900)	(0.0004 ∣ 0.4250, 0.9989 ∣ 0.5750)	(0.0000 ∣ 0.4310, 1.0000 ∣ 0.5690)	(0.0629 ∣ 0.7600, 0.8204 ∣ 0.2400)	(0.0004 ∣ 0.7600, 0.9915 ∣ 0.2400)	(0.9000 ∣ 0.2600, 0.1000 ∣ 0.7400)	(0.9000 ∣ 0.3430, 0.1000 ∣ 0.6570)
CAES	(0.1352 ∣ 0.5600, 0.7527 ∣ 0.4400)	(0.7500 ∣ 0.7400, 0.2000 ∣ 0.2600)	(0.1978 ∣ 0.5300, 0.6045 ∣ 0.4700)	(0.0229 ∣ 0.6520, 0.9543 ∣ 0.3480)	(0.0000 ∣ 0.7640, 1.0000 ∣ 0.2360)	(0.0359 ∣ 0.2390, 0.9282 ∣ 0.7610)	(0.0043 ∣ 0.4860, 0.9872 ∣ 0.5140)	(0.9000 ∣ 0.5660, 0.1000 ∣ 0.4340)	(0.9000 ∣ 0.6240, 0.1000 ∣ 0.3760)
FES	(0.2638 ∣ 0.3500, 0.7032 ∣ 0.6500)	(0.5000 ∣ 0.4340, 0.4500 ∣ 0.5660)	(0.1483 ∣ 0.4260, 0.8022 ∣ 0.5740)	(0.0076 ∣ 0.2390, 0.9771 ∣ 0.7610)	(0.1773 ∣ 0.6400, 0.1137 ∣ 0.3600)	(0.0224 ∣ 0.6000, 0.9686 ∣ 0.4000)	(0.0851 ∣ 0.8000, 0.5744 ∣ 0.2000)	(0.9000 ∣ 0.2470, 0.1000 ∣ 0.7530)	(0.9000 ∣ 0.4400, 0.1000 ∣ 0.5600)
Lead–acid	(0.2473 ∣ 0.3700, 0.7362 ∣ 0.6300)	(0.1000 ∣ 0.7530, 0.9000 ∣ 0.2470)	(0.0297 ∣ 0.6600, 0.8813 ∣ 0.3400)	(0.0229 ∣ 0.6000, 0.9619 ∣ 0.4000)	(0.0009 ∣ 0.6000, 0.9973 ∣ 0.4000)	(0.0269 ∣ 0.7520, 0.9461 ∣ 0.2480)	(0.0128 ∣ 0.7630, 0.9574 ∣ 0.2370)	(0.9000 ∣ 0.6540, 0.1000 ∣ 0.3460)	(0.5000 ∣ 0.5140, 0.4500 ∣ 0.4860)
Li-ion	(0.2143 ∣ 0.6400, 0.7428 ∣ 0.3600)	(0.1000 ∣ 0.5920, 0.9000 ∣ 0.4080)	(0.0494 ∣ 0.6820, 0.8517 ∣ 0.3180)	(0.0572 ∣ 0.2400, 0.8095 ∣ 0.7600)	(0.0009 ∣ 0.2400, 0.9973 ∣ 0.7600)	(0.1078 ∣ 0.5400, 0.6408 ∣ 0.4600)	(0.0511 ∣ 0.6000, 0.7872 ∣ 0.4000)	(0.3500 ∣ 0.2400, 0.6000 ∣ 0.7600)	(0.7500 ∣ 0.2000, 0.2000 ∣ 0.8000)
Hydrogen	(0.1154 ∣ 0.3800, 0.8681 ∣ 0.6200)	(0.5000 ∣ 0.3800, 0.4500 ∣ 0.6200)	(0.0494 ∣ 0.5850, 0.8022 ∣ 0.4150)	(0.6097 ∣ 0.3800, 0.2379 ∣ 0.6200)	(0.0044 ∣ 0.6400, 0.9823 ∣ 0.3600)	(0.0449 ∣ 0.4260, 0.1020 ∣ 0.5740)	(0.0002 ∣ 0.6600, 0.9987 ∣ 0.3400)	(0.7500 ∣ 0.5490, 0.2000 ∣ 0.4510)	(0.5000 ∣ 0.8700, 0.4500 ∣ 0.1300)
Super-capacitors	(0.2803 ∣ 0.7400, 0.6768 ∣ 0.2600)	(0.3500 ∣ 0.7400, 0.6000 ∣ 0.2600)	(0.0989 ∣ 0.8450, 0.7528 ∣ 0.1550)	(0.0001 ∣ 0.7400, 0.9886 ∣ 0.2600)	(0.1773 ∣ 0.3800, 0.6455 ∣ 0.6200)	(0.0090 ∣ 0.5850, 0.9731 ∣ 0.4150)	(0.0255 ∣ 0.6420, 0.8298 ∣ 0.3580)	(0.3500 ∣ 0.5850, 0.6000 ∣ 0.4150)	(0.5000 ∣ 0.6420, 0.4500 ∣ 0.3580)
SMES	(0.2968 ∣ 0.5510, 0.6867 ∣ 0.4490)	(0.3500 ∣ 0.2390, 0.6000 ∣ 0.7610)	(0.1978 ∣ 0.6350, 0.7034 ∣ 0.3650)	(0.0004 ∣ 0.5510, 0.9962 ∣ 0.4490)	(0.0886 ∣ 0.7400, 0.8671 ∣ 0.2600)	(0.0180 ∣ 0.8450, 0.9731 ∣ 0.1550)	(0.0851 ∣ 0.8600, 0.1488 ∣ 0.1400)	(0.9000 ∣ 0.8450, 0.1000 ∣ 0.1550)	(0.5000 ∣ 0.7600, 0.4500 ∣ 0.2400)
Thermal (TES)	(0.0462 ∣ 0.4590, 0.9406 ∣ 0.5410)	(0.7500 ∣ 0.6000, 0.2000 ∣ 0.4000)	(0.0494 ∣ 0.7630, 0.8517 ∣ 0.2370)	(0.0229 ∣ 0.4590, 0.9543 ∣ 0.5410)	(0.0004 ∣ 0.6200, 0.9911 ∣ 0.3800)	(0.0090 ∣ 0.2400, 0.9641 ∣ 0.7600)	(0.0003 ∣ 0.3560, 0.9889 ∣ 0.6440)	(0.3500 ∣ 0.6350, 0.6000 ∣ 0.3650)	(0.5000 ∣ 0.4700, 0.4500 ∣ 0.5300)

Table A5. Decision basic data of Expert 4.

Technologies	Energy Efficiency (%)	Response Time	Lifetime (Years)	Energy Density (Wh/kg)	Self-Discharge Losses (%/Day)	Power Capital Cost (USD/kw)	Energy Capital Cost (USD/kwh)	Environmental Dimension	Social Acceptance
PHS	(65, 75)	Medium	(30, 60)	(0.5, 1.5)	(0.0001, 0.0001)	(600, 2000)	(5, 100)	Very high	Very high
CAES	(41, 75)	Long	(20, 40)	(30, 60)	(0.0001, 0.0001)	(400, 800)	(50, 150)	Very high	Very high
FES	(80, 90)	Medium	(15, 20)	(5, 50)	(20, 100)	(250, 350)	(1000, 5000)	Very high	Very high
Lead–acid	(75, 80)	Very short	(3, 12)	(30, 50)	(0.1, 0.3)	(300, 600)	(150, 500)	Very high	Medium
Li-ion	(65, 75)	Very short	(5, 15)	(75, 250)	(0.1, 0.3)	(1200, 4000)	(600, 2500)	Low	High
Hydrogen	(35, 40)	Medium	(5, 20)	(800, 1000)	(0.5, 2)	(500, 10,000)	(2, 15)	High	Medium
Super-capacitors	(85, 98)	Short	(10, 20)	(0.1, 15)	(20, 40)	(100, 300)	(300, 2000)	Low	Medium
SMES	(90, 95)	Short	(20, 30)	(0.5, 5)	(10, 15)	(200, 300)	(1000, 10,000)	Very high	Medium
Thermal (TES)	(14, 18)	Long	(5, 15)	(30, 60)	(0.05, 1)	(100, 400)	(3, 130)	Low	Medium

Table A6. Initial decision matric of Expert 4.

<table>
<tr><th>Technologies</th><th>Energy Efficiency (%)</th><th>Response Time</th><th>Lifetime (Years)</th><th>Energy Density (Wh/kg)</th><th>Self-Discharge Losses (%/Day)</th><th>Power Capital Cost (USD/kw)</th><th>Energy Capital Cost (USD/kwh)</th><th>Environmental Dimension</th><th>Social Acceptance</th></tr>
<tr><td>PHS</td><td>(0.2157 | 0.7400, 0.7511 | 0.2600)</td><td>(0.5000 | 0.5600, 0.4500 | 0.4400)</td><td>(0.3000 | 0.5600, 0.4001 | 0.4400)</td><td>(0.0004 | 0.5920, 0.9989 | 0.4080)</td><td>(0.0000 | 0.7600, 1.0000 | 0.2400)</td><td>(0.0539 | 0.3900, 0.8203 | 0.6100)</td><td>(0.0004 | 0.7000, 0.9915 | 0.3000)</td><td>(0.9000 | 0.8820, 0.1000 | 0.1180)</td><td>(0.9000 | 0.4300, 0.1000 | 0.5700)</td></tr>
<tr><td>CAES</td><td>(0.1360 | 0.5510, 0.7511 | 0.4490)</td><td>(0.7500 | 0.5490, 0.2000 | 0.4510)</td><td>(0.2000 | 0.5490, 0.6001 | 0.4510)</td><td>(0.0229 | 0.5490, 0.9543 | 0.4510)</td><td>(0.0000 | 0.4600, 1.0000 | 0.5400)</td><td>(0.0359 | 0.7800, 0.9281 | 0.2200)</td><td>(0.0043 | 0.5320, 0.9872 | 0.4680)</td><td>(0.9000 | 0.3050, 0.1000 | 0.6950)</td><td>(0.9000 | 0.6250, 0.1000 | 0.3750)</td></tr>
<tr><td>FES</td><td>(0.2654 | 0.7600, 0.7014 | 0.2400)</td><td>(0.5000 | 0.2390, 0.4500 | 0.7610)</td><td>(0.15000 | 0.2390, 0.8000 | 0.7610)</td><td>(0.0038 | 0.2390, 0.9619 | 0.7610)</td><td>(0.1773 | 0.6520, 0.1137 | 0.3480)</td><td>(0.0225 | 0.4500, 0.9686 | 0.5500)</td><td>(0.0851 | 0.6930, 0.5744 | 0.3070)</td><td>(0.9000 | 0.4400, 0.1000 | 0.5600)</td><td>(0.9000 | 0.6520, 0.1000 | 0.3480)</td></tr>
<tr><td>Lead–acid</td><td>(0.2489 | 0.2390, 0.7346 | 0.7610)</td><td>(0.1000 | 0.6000, 0.9000 | 0.4000)</td><td>(0.0300 | 0.6000, 0.8800 | 0.4000)</td><td>(0.0229 | 0.6000, 0.9619 | 0.4000)</td><td>(0.0009 | 0.2390, 0.9973 | 0.7610)</td><td>(0.0270 | 0.4900, 0.9461 | 0.5100)</td><td>(0.0128 | 0.2390, 0.9574 | 0.7610)</td><td>(0.9000 | 0.2000, 0.1000 | 0.8000)</td><td>(0.5000 | 0.2390, 0.4500 | 0.7610)</td></tr>
<tr><td>Li-ion</td><td>(0.2157 | 0.6000, 0.7511 | 0.4000)</td><td>(0.1000 | 0.3900, 0.9000 | 0.6100)</td><td>(0.0500 | 0.5920, 0.8500 | 0.4080)</td><td>(0.0571 | 0.5920, 0.8096 | 0.4080)</td><td>(0.0009 | 0.6000, 0.9973 | 0.4000)</td><td>(0.1078 | 0.2700, 0.6406 | 0.7300)</td><td>(0.0511 | 0.6000, 0.7872 | 0.4000)</td><td>(0.3500 | 0.5600, 0.6000 | 0.4400)</td><td>(0.7500 | 0.6000, 0.2000 | 0.4000)</td></tr>
<tr><td>Hydrogen</td><td>(0.1161 | 0.2700, 0.8673 | 0.7300)</td><td>(0.5000 | 0.7800, 0.4500 | 0.2200)</td><td>(0.0500 | 0.7800, 0.8000 | 0.2200)</td><td>(0.6094 | 0.5920, 0.2382 | 0.4080)</td><td>(0.0044 | 0.2400, 0.9823 | 0.7600)</td><td>(0.0449 | 0.7200, 0.1016 | 0.2800)</td><td>(0.0002 | 0.5490, 0.9987 | 0.4510)</td><td>(0.7500 | 0.5490, 0.2000 | 0.4510)</td><td>(0.5000 | 0.5490, 0.4500 | 0.4510)</td></tr>
<tr><td>Super-capacitors</td><td>(0.2820 | 0.7200, 0.6748 | 0.2800)</td><td>(0.3500 | 0.4500, 0.6000 | 0.5500)</td><td>(0.1000 | 0.4500, 0.8000 | 0.5500)</td><td>(0.0001 | 0.4500, 0.9886 | 0.5500)</td><td>(0.1773 | 0.5550, 0.6455 | 0.4450)</td><td>(0.0090 | 0.3380, 0.9730 | 0.5850)</td><td>(0.0255 | 0.6820, 0.8298 | 0.3180)</td><td>(0.3500 | 0.8300, 0.6000 | 0.1700)</td><td>(0.5000 | 0.8300, 0.4500 | 0.1700)</td></tr>
<tr><td>SMES</td><td>(0.2986 | 0.5490, 0.6848 | 0.4510)</td><td>(0.3500 | 0.5850, 0.6000 | 0.4150)</td><td>(0.2000 | 0.5850, 0.7000 | 0.4150)</td><td>(0.0004 | 0.5850, 0.9962 | 0.4150)</td><td>(0.0886 | 0.4900, 0.8671 | 0.5100)</td><td>(0.0180 | 0.8600, 0.9730 | 0.8450)</td><td>(0.0851 | 0.5850, 0.1488 | 0.4150)</td><td>(0.9000 | 0.8590, 0.1000 | 0.1410)</td><td>(0.5000 | 0.7340, 0.4500 | 0.2660)</td></tr>
<tr><td>Thermal (TES)</td><td>(0.0465 | 0.5850, 0.9403 | 0.4150)</td><td>(0.7500 | 0.8450, 0.2000 | 0.1550)</td><td>(0.0500 | 0.8450, 0.8500 | 0.1550)</td><td>(0.0229 | 0.4590, 0.9543 | 0.5410)</td><td>(0.0004 | 0.3100, 0.9911 | 0.6900)</td><td>(0.0090 | 0.2590, 0.9641 | 0.6350)</td><td>(0.0003 | 0.7900, 0.9889 | 0.2100)</td><td>(0.3500 | 0.4300, 0.6000 | 0.5700)</td><td>(0.5000 | 0.3700, 0.4500 | 0.6300)</td></tr>
</table>

Table A7. Decision basic data of Expert 5.

Technologies	Energy Efficiency (%)	Response Time	Lifetime (Years)	Energy Density (Wh/kg)	Self-Discharge Losses (%/Day)	Power Capital Cost (USD/kw)	Energy Capital Cost (USD/kwh)	Environmental Dimension	Social Acceptance
PHS	(65, 75)	Medium	(30, 60)	(0.5, 1.5)	(0.0001, 0.0001)	(600, 4600)	(5, 100)	Very high	Very high
CAES	(41, 75)	Long	(20, 40)	(30, 60)	(0.0001, 0.0001)	(400, 800)	(50, 150)	Very high	Very high
FES	(80, 90)	Medium	(15, 20)	(10, 30)	(20, 100)	(250, 350)	(1000, 5000)	Very high	Very high
Lead–acid	(70, 80)	Very short	(3, 12)	(30, 50)	(0.1, 0.3)	(300, 600)	(150, 500)	Very high	Medium
Li-ion	(65, 75)	Very short	(5, 15)	(75, 250)	(0.1, 0.3)	(1200, 4000)	(600, 2500)	Low	High
Hydrogen	(35, 40)	Medium	(5, 20)	(800, 1000)	(0.5, 2)	(500, 10,000)	(2, 15)	High	Medium
Super-capacitors	(85, 98)	Short	(10, 20)	(0.1, 15)	(20, 40)	(100, 300)	(300, 2000)	Low	Medium
SMES	(90, 95)	Short	(20, 30)	(0.5, 5)	(10, 15)	(200, 300)	(1000, 10,000)	Very high	Medium
Thermal (TES)	(14, 18)	Long	(5, 15)	(30, 60)	(0.05, 1)	(100, 400)	(3, 130)	Low	Medium

Table A8. Initial decision matric of Expert 5.

Technologies	Energy Efficiency (%)	Response Time	Lifetime (Years)	Energy Density (Wh/kg)	Self-Discharge Losses (%/Day)	Power Capital Cost (USD/kw)	Energy Capital Cost (USD/kwh)	Environmental Dimension	Social Acceptance
PHS	(0.2156 | 0.6750, 0.7513 | 0.3250)	(0.5000 | 0.3750, 0.4500 | 0.6250)	(0.3026 | 0.6850, 0.3948 | 0.3150)	(0.0004 | 0.5400, 0.9989 | 0.4600)	(0.0000 | 0.5430, 1.0000 | 0.4570)	(0.0539 | 0.3590, 0.8203 | 0.6410)	(0.0004 | 0.4570, 0.9915 | 0.5430)	(0.9000 | 0.7820, 0.1000 | 0.2180)	(0.9000 | 0.6430, 0.1000 | 0.3570)
CAES	(0.1360 | 0.5450, 0.7513 | 0.4550)	(0.7500 | 0.5650, 0.2000 | 0.4350)	(0.2017 | 0.4670, 0.5965 | 0.5330)	(0.0229 | 0.4320, 0.9543 | 0.5680)	(0.0000 | 0.3460, 1.0000 | 0.6540)	(0.0359 | 0.6780, 0.9281 | 0.3220)	(0.0043 | 0.6720, 0.9872 | 0.3280)	(0.9000 | 0.3000, 0.1000 | 0.7000)	(0.9000 | 0.4500, 0.1000 | 0.5500)
FES	(0.2819 | 0.6500, 0.7015 | 0.3500)	(0.5000 | 0.7240, 0.4500 | 0.2760)	(0.1513 | 0.5400, 0.7983 | 0.4600)	(0.0076 | 0.7970, 0.9771 | 0.2030)	(0.1773 | 0.6560, 0.1137 | 0.3440)	(0.0225 | 0.4500, 0.9686 | 0.5500)	(0.0851 | 0.6930, 0.5744 | 0.3070)	(0.9000 | 0.5400, 0.1000 | 0.4600)	(0.9000 | 0.4200, 0.1000 | 0.5800)
Lead–acid	(0.2321 | 0.7420, 0.7347 | 0.2580)	(0.1000 | 0.4570, 0.9000 | 0.5430)	(0.0303 | 0.3500, 0.8790 | 0.6500)	(0.0229 | 0.7160, 0.9619 | 0.2840)	(0.0009 | 0.7400, 0.9973 | 0.2600)	(0.0270 | 0.6850, 0.9461 | 0.3150)	(0.0128 | 0.2400, 0.9574 | 0.7600)	(0.9000 | 0.2900, 0.1000 | 0.7100)	(0.5000 | 0.4670, 0.4500 | 0.5330)
Li-ion	(0.2156 | 0.7240, 0.7513 | 0.2760)	(0.1000 | 0.6720, 0.9000 | 0.3280)	(0.0504 | 0.5400, 0.8487 | 0.4600)	(0.0572 | 0.2400, 0.8095 | 0.7600)	(0.0009 | 0.4800, 0.9973 | 0.5200)	(0.1078 | 0.4670, 0.6406 | 0.5330)	(0.0511 | 0.5400, 0.7872 | 0.4600)	(0.3500 | 0.4600, 0.6000 | 0.5400)	(0.7500 | 0.3700, 0.2000 | 0.6300)
Hydrogen	(0.1161 | 0.5400, 0.8674 | 0.4600)	(0.5000 | 0.5600, 0.4500 | 0.4400)	(0.0504 | 0.3940, 0.8487 | 0.6060)	(0.6097 | 0.6430, 0.2379 | 0.3570)	(0.0044 | 0.3430, 0.9823 | 0.6570)	(0.0449 | 0.5400, 0.1016 | 0.4600)	(0.0002 | 0.5400, 0.9987 | 0.4600)	(0.7500 | 0.5490, 0.2000 | 0.4510)	(0.5000 | 0.6420, 0.4500 | 0.3580)
Super-capacitors	(0.2819 | 0.6520, 0.6750 | 0.3480)	(0.3500 | 0.8700, 0.6000 | 0.1300)	(0.1009 | 0.4830, 0.7983 | 0.5170)	(0.0001 | 0.5400, 0.9886 | 0.4600)	(0.1773 | 0.7550, 0.6455 | 0.2450)	(0.0090 | 0.7550, 0.9730 | 0.2450)	(0.0255 | 0.6200, 0.8298 | 0.3800)	(0.3500 | 0.4300, 0.6000 | 0.5700)	(0.5000 | 0.4800, 0.4500 | 0.5200)
SMES	(0.2985 | 0.7520, 0.6850 | 0.2480)	(0.3500 | 0.1900, 0.6000 | 0.8100)	(0.2017 | 0.2100, 0.6974 | 0.7900)	(0.0004 | 0.5540, 0.9962 | 0.4460)	(0.0886 | 0.4900, 0.8671 | 0.5100)	(0.0180 | 0.4900, 0.9730 | 0.5100)	(0.0851 | 0.8500, 0.1488 | 0.1500)	(0.9000 | 0.5900, 0.1000 | 0.4100)	(0.5000 | 0.7970, 0.4500 | 0.2030)
Thermal (TES)	(0.0464 | 0.4730, 0.9403 | 0.5270)	(0.7500 | 0.7120, 0.2000 | 0.2880)	(0.0504 | 0.1750, 0.8487 | 0.8250)	(0.0229 | 0.3400, 0.9543 | 0.6600)	(0.0004 | 0.5310, 0.9911 | 0.4690)	(0.0090 | 0.5310, 0.9641 | 0.4690)	(0.0003 | 0.8900, 0.9889 | 0.1100)	(0.3500 | 0.3430, 0.6000 | 0.6570)	(0.5000 | 0.7160, 0.4500 | 0.2840)

Table A9. Decision basic data of Expert 6.

Technologies	Energy Efficiency (%)	Response Time	Lifetime (Years)	Energy Density (Wh/kg)	Self-Discharge Losses (%/Day)	Power Capital Cost (USD/kw)	Energy Capital Cost (USD/kwh)	Environmental Dimension	Social Acceptance
PHS	(65, 75)	Medium	(30, 60)	(0.5, 1.5)	(0.0001, 0.0001)	(600, 2000)	(5, 100)	Very high	Very high
CAES	(41, 75)	Long	(20, 40)	(30, 60)	(0.0001, 0.0001)	(400, 800)	(50, 150)	Very high	Very high
FES	(80, 90)	Medium	(15, 20)	(10, 30)	(20, 100)	(250, 350)	(1000, 5000)	Very high	Very high
Lead–acid	(75, 80)	Very short	(3, 12)	(30, 50)	(0.1, 0.3)	(300, 600)	(150, 500)	Very high	Medium
Li-ion	(65, 75)	Very short	(5, 15)	(75, 250)	(0.1, 0.3)	(1200, 4000)	(600, 2500)	Low	High
Hydrogen	(35, 40)	Medium	(5, 15)	(800, 1000)	(0.5, 2)	(500, 10,000)	(2, 15)	High	Medium
Super-capacitors	(85, 98)	Short	(10, 20)	(0.1, 15)	(20, 40)	(100, 300)	(300, 2000)	Low	Medium
SMES	(90, 95)	Short	(20, 30)	(0.5, 5)	(10, 15)	(200, 300)	(1000, 10,000)	Very high	Medium
Thermal (TES)	(14, 18)	Long	(5, 15)	(30, 60)	(0.05, 1)	(100, 400)	(3, 130)	Low	Medium

Table A10. Initial decision matrix of Expert 6.

Technologies	Energy Efficiency (%)	Response Time	Lifetime (Years)	Energy Density (Wh/kg)	Self-Discharge Losses (%/Day)	Power Capital Cost (USD/kw)	Energy Capital Cost (USD/kwh)	Environmental Dimension	Social Acceptance
PHS	(0.2157 | 0.4450, 0.7511 | 0.5550)	(0.5000 | 0.4040, 0.4500 | 0.5960)	(0.3026 | 0.6570, 0.3948 | 0.3430)	(0.0004 | 0.4000, 0.9989 | 0.6000)	(0.0000 | 0.5420, 1.0000 | 0.4580)	(0.0539 | 0.5640, 0.8203 | 0.4360)	(0.0004 | 0.7400, 0.9915 | 0.2600)	(0.9000 | 0.4460, 0.1000 | 0.5540)	(0.9000 | 0.4030, 0.1000 | 0.5970)
CAES	(0.1360 | 0.5300, 0.7511 | 0.4700)	(0.7500 | 0.5560, 0.2000 | 0.4440)	(0.2017 | 0.3760, 0.5965 | 0.6240)	(0.0229 | 0.6100, 0.9543 | 0.3900)	(0.0000 | 0.7500, 1.0000 | 0.2500)	(0.0359 | 0.6500, 0.9281 | 0.3500)	(0.0043 | 0.5320, 0.9872 | 0.4680)	(0.9000 | 0.5400, 0.1000 | 0.4600)	(0.9000 | 0.6470, 0.1000 | 0.3530)
FES	(0.2654 | 0.4300, 0.7014 | 0.5700)	(0.5000 | 0.8630, 0.4500 | 0.1370)	(0.1513 | 0.4600, 0.7983 | 0.5400)	(0.0076 | 0.2200, 0.9771 | 0.7800)	(0.1773 | 0.3660, 0.1137 | 0.6340)	(0.0225 | 0.4500, 0.9686 | 0.5500)	(0.0851 | 0.4600, 0.5744 | 0.5400)	(0.9000 | 0.6440, 0.1000 | 0.3560)	(0.9000 | 0.4110, 0.1000 | 0.5890)
Lead–acid	(0.2489 | 0.7700, 0.7346 | 0.2300)	(0.1000 | 0.7520, 0.9000 | 0.2480)	(0.0303 | 0.4600, 0.8790 | 0.5400)	(0.0229 | 0.4110, 0.9619 | 0.5890)	(0.0009 | 0.6340, 0.9973 | 0.3660)	(0.0270 | 0.4900, 0.9461 | 0.5100)	(0.0128 | 0.4600, 0.9574 | 0.5400)	(0.9000 | 0.2420, 0.1000 | 0.7580)	(0.5000 | 0.4670, 0.4500 | 0.5330)
Li-ion	(0.2157 | 0.3240, 0.7511 | 0.6760)	(0.1000 | 0.5750, 0.9000 | 0.4250)	(0.0504 | 0.6340, 0.8487 | 0.3660)	(0.0572 | 0.2640, 0.8095 | 0.7360)	(0.0009 | 0.6600, 0.9973 | 0.3400)	(0.1078 | 0.4270, 0.6406 | 0.5730)	(0.0511 | 0.6340, 0.7872 | 0.3660)	(0.3500 | 0.5600, 0.6000 | 0.4400)	(0.7500 | 0.6700, 0.2000 | 0.3300)
Hydrogen	(0.1161 | 0.3980, 0.8673 | 0.6020)	(0.5000 | 0.3460, 0.4500 | 0.6540)	(0.0504 | 0.3980, 0.8487 | 0.6020)	(0.6097 | 0.5800, 0.2379 | 0.4200)	(0.0044 | 0.6410, 0.9823 | 0.3590)	(0.0449 | 0.6470, 0.1016 | 0.3530)	(0.0002 | 0.4400, 0.9987 | 0.5600)	(0.7500 | 0.5400, 0.2000 | 0.4600)	(0.5000 | 0.8070, 0.4500 | 0.1930)
Super-capacitors	(0.2820 | 0.6000, 0.6748 | 0.4000)	(0.3500 | 0.2400, 0.6000 | 0.7600)	(0.1009 | 0.4600, 0.7983 | 0.5400)	(0.0001 | 0.4270, 0.9886 | 0.5730)	(0.1773 | 0.4500, 0.6455 | 0.5500)	(0.0090 | 0.6800, 0.9730 | 0.3200)	(0.0255 | 0.5600, 0.8298 | 0.4400)	(0.3500 | 0.8300, 0.6000 | 0.1700)	(0.5000 | 0.4260, 0.4500 | 0.5740)
SMES	(0.2986 | 0.7100, 0.6848 | 0.2900)	(0.3500 | 0.1940, 0.6000 | 0.8060)	(0.2017 | 0.6340, 0.6974 | 0.3660)	(0.0004 | 0.2420, 0.9962 | 0.7580)	(0.0886 | 0.4900, 0.8671 | 0.5100)	(0.0180 | 0.8640, 0.9730 | 0.1360)	(0.0851 | 0.5400, 0.1488 | 0.4600)	(0.9000 | 0.8900, 0.1000 | 0.1100)	(0.5000 | 0.6400, 0.4500 | 0.3600)
Thermal (TES)	(0.0465 | 0.3200, 0.9403 | 0.6800)	(0.7500 | 0.4400, 0.2000 | 0.5600)	(0.0504 | 0.6600, 0.8487 | 0.3400)	(0.0229 | 0.6470, 0.9543 | 0.3530)	(0.0004 | 0.2310, 0.9911 | 0.7690)	(0.0090 | 0.6530, 0.9641 | 0.3470)	(0.0003 | 0.7200, 0.9889 | 0.2800)	(0.3500 | 0.4300, 0.6000 | 0.5700)	(0.5000 | 0.4100, 0.4500 | 0.5900)

Table A11. Decision basic data of Expert 7.

Technologies	Energy Efficiency (%)	Response Time	Lifetime (Years)	Energy Density (Wh/kg)	Self-Discharge Losses (%/Day)	Power Capital Cost (USD/kw)	Energy Capital Cost (USD/kwh)	Environmental Dimension	Social Acceptance
PHS	(75, 80)	Medium	(30, 60)	(0.5, 1.5)	(0.0001, 0.0001)	(600, 2000)	(5, 100)	Very high	Very high
CAES	(41, 75)	Long	(20, 40)	(30, 60)	(0.0001, 0.0001)	(400, 800)	(50, 150)	Very high	Very high
FES	(88, 90)	Medium	(15, 20)	(5, 130)	(20, 100)	(250, 350)	(1000, 5000)	Very high	Very high
Lead–acid	(75, 80)	Very short	(3, 12)	(30, 50)	(0.1, 0.3)	(300, 600)	(150, 500)	Very high	Medium
Li-ion	(65, 75)	Very short	(5, 15)	(75, 250)	(0.1, 0.3)	(1200, 4000)	(600, 2500)	Low	High
Hydrogen	(35, 40)	Medium	(5, 15)	(800, 1000)	(0.5, 2)	(500, 10,000)	(2, 15)	High	Medium
Super-capacitors	(85, 98)	Short	(10, 20)	(0.1, 15)	(20, 40)	(100, 300)	(300, 2000)	Low	Medium
SMES	(90, 95)	Short	(20, 30)	(0.5, 5)	(10, 15)	(200, 300)	(1000, 10,000)	Very high	Medium
Thermal (TES)	(14, 18)	Long	(5, 15)	(30, 60)	(0.05, 1)	(100, 400)	(3, 130)	Low	Medium

Table A12. Initial decision matrix of Expert 7.

<table>
<tr><th>Technologies</th><th>Energy Efficiency (%)</th><th>Response Time</th><th>Lifetime (Years)</th><th>Energy Density (Wh/kg)</th><th>Self-Discharge Losses (%/Day)</th><th>Power Capital Cost (USD/kw)</th><th>Energy Capital Cost (USD/kwh)</th><th>Environmental Dimension</th><th>Social Acceptance</th></tr>
<tr><td>PHS</td><td>(0.2442 | 0.7610, 0.7396 | 0.2390)</td><td>(0.5000 | 0.5500, 0.4500 | 0.4500)</td><td>(0.3026 | 0.5250, 0.3948 | 0.4750)</td><td>(0.0004 | 0.8790, 0.9989 | 0.1210)</td><td>(0.0000 | 0.6250, 1.0000 | 0.3750)</td><td>(0.0539 | 0.4300, 0.8203 | 0.5700)</td><td>(0.0004 | 0.6200, 0.9915 | 0.3800)</td><td>(0.9000 | 0.8800, 0.1000 | 0.1200)</td><td>(0.9000 | 0.5420, 0.1000 | 0.4580)</td></tr>
<tr><td>CAES</td><td>(0.1335 | 0.4000, 0.7558 | 0.6000)</td><td>(0.7500 | 0.5100, 0.2000 | 0.4900)</td><td>(0.2017 | 0.6520, 0.5965 | 0.3480)</td><td>(0.0228 | 0.4670, 0.9545 | 0.5330)</td><td>(0.0000 | 0.5420, 1.0000 | 0.4580)</td><td>(0.0359 | 0.6250, 0.9281 | 0.3750)</td><td>(0.0043 | 0.4800, 0.9872 | 0.5200)</td><td>(0.9000 | 0.3050, 0.1000 | 0.6950)</td><td>(0.9000 | 0.6020, 0.1000 | 0.3980)</td></tr>
<tr><td>FES</td><td>(0.2865 | 0.4510, 0.7070 | 0.5490)</td><td>(0.5000 | 0.5320, 0.4500 | 0.4680)</td><td>(0.1513 | 0.2390, 0.7983 | 0.7610)</td><td>(0.0038 | 0.7700, 0.9014 | 0.2300)</td><td>(0.1773 | 0.2360, 0.1137 | 0.7640)</td><td>(0.0225 | 0.2390, 0.9686 | 0.7610)</td><td>(0.0851 | 0.6600, 0.5744 | 0.3400)</td><td>(0.9000 | 0.4400, 0.1000 | 0.5600)</td><td>(0.9000 | 0.5400, 0.1000 | 0.4600)</td></tr>
<tr><td>Lead–acid</td><td>(0.2442 | 0.6100, 0.7396 | 0.3900)</td><td>(0.1000 | 0.6930, 0.9000 | 0.3070)</td><td>(0.0303 | 0.6000, 0.8790 | 0.4000)</td><td>(0.0228 | 0.4400, 0.9621 | 0.5600)</td><td>(0.0009 | 0.7000, 0.9973 | 0.3000)</td><td>(0.0270 | 0.6000, 0.9461 | 0.4000)</td><td>(0.0128 | 0.2390, 0.9574 | 0.7610)</td><td>(0.9000 | 0.6100, 0.1000 | 0.3900)</td><td>(0.5000 | 0.4670, 0.4500 | 0.5330)</td></tr>
<tr><td>Li-ion</td><td>(0.2116 | 0.3900, 0.7558 | 0.6100)</td><td>(0.1000 | 0.5920, 0.9000 | 0.4080)</td><td>(0.0504 | 0.6100, 0.8487 | 0.3900)</td><td>(0.0569 | 0.6100, 0.8104 | 0.3900)</td><td>(0.0009 | 0.3180, 0.9973 | 0.6820)</td><td>(0.1078 | 0.6100, 0.6406 | 0.3900)</td><td>(0.0511 | 0.6000, 0.7872 | 0.4000)</td><td>(0.3500 | 0.3900, 0.6000 | 0.6100)</td><td>(0.7500 | 0.3900, 0.2000 | 0.6100)</td></tr>
<tr><td>Hydrogen</td><td>(0.1139 | 0.6020, 0.8698 | 0.3980)</td><td>(0.5000 | 0.3360, 0.4500 | 0.6640)</td><td>(0.0504 | 0.3900, 0.8487 | 0.6100)</td><td>(0.6069 | 0.3800, 0.2414 | 0.6200)</td><td>(0.0044 | 0.4150, 0.9823 | 0.5850)</td><td>(0.0449 | 0.7200, 0.1016 | 0.2800)</td><td>(0.0002 | 0.6000, 0.9987 | 0.4000)</td><td>(0.7500 | 0.4830, 0.2000 | 0.5170)</td><td>(0.5000 | 0.4830, 0.4500 | 0.5170)</td></tr>
<tr><td>Super-capacitors</td><td>(0.2767 | 0.5400, 0.6810 | 0.4600)</td><td>(0.3500 | 0.2700, 0.6000 | 0.7300)</td><td>(0.1009 | 0.4830, 0.7983 | 0.5170)</td><td>(0.0001 | 0.7400, 0.9886 | 0.2600)</td><td>(0.1773 | 0.2100, 0.6455 | 0.4400)</td><td>(0.0090 | 0.3380, 0.9730 | 0.5400)</td><td>(0.0255 | 0.6100, 0.8298 | 0.3900)</td><td>(0.3500 | 0.8300, 0.6000 | 0.1700)</td><td>(0.5000 | 0.8300, 0.4500 | 0.1700)</td></tr>
<tr><td>SMES</td><td>(0.2930 | 0.7110, 0.6907 | 0.2890)</td><td>(0.3500 | 0.5550, 0.6000 | 0.4450)</td><td>(0.2017 | 0.2160, 0.6974 | 0.7840)</td><td>(0.0004 | 0.2160, 0.9962 | 0.7840)</td><td>(0.0886 | 0.4900, 0.8671 | 0.5100)</td><td>(0.0180 | 0.8600, 0.9730 | 0.7340)</td><td>(0.0851 | 0.5850, 0.1488 | 0.4150)</td><td>(0.9000 | 0.5320, 0.1000 | 0.4680)</td><td>(0.5000 | 0.7340, 0.4500 | 0.2660)</td></tr>
<tr><td>Thermal (TES)</td><td>(0.0456 | 0.2400, 0.9414 | 0.7600)</td><td>(0.7500 | 0.4900, 0.2000 | 0.5100)</td><td>(0.0504 | 0.1500, 0.8487 | 0.8500)</td><td>(0.0228 | 0.1500, 0.9545 | 0.8500)</td><td>(0.0004 | 0.3100, 0.9911 | 0.6900)</td><td>(0.0090 | 0.2590, 0.9641 | 0.3700)</td><td>(0.0003 | 0.7900, 0.9889 | 0.2100)</td><td>(0.3500 | 0.6930, 0.6000 | 0.3070)</td><td>(0.5000 | 0.4600, 0.4500 | 0.5400)</td></tr>
</table>

Table A13. Decision basic data of Expert 8.

Technologies	Energy Efficiency (%)	Response Time	Lifetime (Years)	Energy Density Wh/kg	Self-Discharge Losses (%/Day)	Power Capital Cost (USD/kw)	Energy Capital Cost (USD/kwh)	Environmental Dimension	Social Acceptance
PHS	(65, 75)	Medium	(30, 60)	(0.5, 1.5)	(0.0001, 0.0001)	(600, 2000)	(5, 100)	Very high	Very high
CAES	(41, 75)	Long	(20, 40)	(30, 60)	(0.0001, 0.0001)	(400, 800)	(50, 150)	Very high	Very high
FES	(80, 90)	Medium	(15, 20)	(5, 130)	(20, 100)	(250, 350)	(1000, 5000)	Very high	Very high
Lead–acid	(75, 80)	Very short	(3, 12)	(30, 50)	(0.1, 0.3)	(300, 600)	(150, 500)	Very high	Medium
Li-ion	(65, 78)	Very short	(5, 15)	(75, 250)	(0.1, 0.3)	(1200, 4000)	(600, 2500)	Low	High
Hydrogen	(35, 40)	Medium	(5, 15)	(800, 1000)	(0.5, 2)	(500, 10,000)	(2, 15)	High	Medium
Super-capacitors	(85, 98)	Short	(10, 20)	(0.1, 15)	(20, 40)	(100, 300)	(300, 2000)	Low	Medium
SMES	(90, 95)	Short	(20, 30)	(0.5, 5)	(10, 15)	(200, 300)	(1000, 10,000)	Very high	Medium
Thermal (TES)	(14, 18)	Long	(5, 15)	(30, 60)	(0.05, 1)	(100, 400)	(3, 130)	Low	Medium

Table A14. Initial decision matrix of Expert 8.

Technologies	Energy Efficiency (%)	Response Time	Lifetime (Years)	Energy Density (Wh/kg)	Self-Discharge Losses (%/Day)	Power Capital Cost (USD/kw)	Energy Capital Cost (USD/kwh)	Environmental Dimension	Social Acceptance
PHS	(0.2151 ǀ 0.6100, 0.7518 ǀ 0.3900)	(0.5000 ǀ 0.4600, 0.4500 ǀ 0.5400)	(0.3026 ǀ 0.7800, 0.3948 ǀ 0.2200)	(0.0004 ǀ 0.7160, 0.9989 ǀ 0.2840)	(0.0000 ǀ 0.6400, 1.0000 ǀ 0.3600)	(0.0539 ǀ 0.5460, 0.8203 ǀ 0.4540)	(0.0004 ǀ 0.7540, 0.9915 ǀ 0.2460)	(0.9000 ǀ 0.8000, 0.1000 ǀ 0.2000)	(0.9000 ǀ 0.5430, 0.1000 ǀ 0.4570)
CAES	(0.1357 ǀ 0.3900, 0.7518 ǀ 0.6100)	(0.7500 ǀ 0.6340, 0.2000 ǀ 0.3660)	(0.2017 ǀ 0.4500, 0.5965 ǀ 0.5500)	(0.0228 ǀ 0.2400, 0.9545 ǀ 0.7600)	(0.0000 ǀ 0.5630, 1.0000 ǀ 0.4370)	(0.0359 ǀ 0.7540, 0.9281 ǀ 0.2460)	(0.0043 ǀ 0.5320, 0.9872 ǀ 0.4680)	(0.9000 ǀ 0.3800, 0.1000 ǀ 0.6200)	(0.9000 ǀ 0.7250, 0.1000 ǀ 0.2750)
FES	(0.2648 ǀ 0.5400, 0.7021 ǀ 0.4600)	(0.5000 ǀ 0.5400, 0.4500 ǀ 0.4600)	(0.1513 ǀ 0.4900, 0.7983 ǀ 0.5100)	(0.0038 ǀ 0.6430, 0.9014 ǀ 0.3570)	(0.1773 ǀ 0.3460, 0.1137 ǀ 0.6540)	(0.0225 ǀ 0.4500, 0.9686 ǀ 0.5500)	(0.0851 ǀ 0.6930, 0.5744 ǀ 0.3070)	(0.9000 ǀ 0.4320, 0.1000 ǀ 0.5680)	(0.9000 ǀ 0.5400, 0.1000 ǀ 0.4600)
Lead–acid	(0.2482 ǀ 0.3940, 0.7352 ǀ 0.6060)	(0.1000 ǀ 0.5510, 0.9000 ǀ 0.4490)	(0.0303 ǀ 0.7200, 0.8790 ǀ 0.2800)	(0.0228 ǀ 0.7110, 0.9621 ǀ 0.2890)	(0.0009 ǀ 0.6400, 0.9973 ǀ 0.3600)	(0.0270 ǀ 0.4120, 0.9461 ǀ 0.5880)	(0.0128 ǀ 0.2300, 0.9574 ǀ 0.7700)	(0.9000 ǀ 0.2800, 0.1000 ǀ 0.7200)	(0.5000 ǀ 0.4700, 0.4500 ǀ 0.5300)
Li-ion	(0.2151 ǀ 0.3200, 0.7418 ǀ 0.6800)	(0.1000 ǀ 0.7800, 0.9000 ǀ 0.2200)	(0.0504 ǀ 0.6930, 0.8487 ǀ 0.3070)	(0.0569 ǀ 0.6930, 0.8104 ǀ 0.3070)	(0.0009 ǀ 0.4880, 0.9973 ǀ 0.5120)	(0.1078 ǀ 0.2700, 0.6406 ǀ 0.7300)	(0.0511 ǀ 0.6000, 0.7872 ǀ 0.4000)	(0.3500 ǀ 0.5110, 0.6000 ǀ 0.4890)	(0.7500 ǀ 0.5670, 0.2000 ǀ 0.4330)
Hydrogen	(0.1158 ǀ 0.4800, 0.8676 ǀ 0.5200)	(0.5000 ǀ 0.4500, 0.4500 ǀ 0.5500)	(0.0504 ǀ 0.2390, 0.8487 ǀ 0.7610)	(0.6069 ǀ 0.2700, 0.2414 ǀ 0.7300)	(0.0044 ǀ 0.3300, 0.9823 ǀ 0.6700)	(0.0449 ǀ 0.7200, 0.1016 ǀ 0.2800)	(0.0002 ǀ 0.5490, 0.9987 ǀ 0.4510)	(0.7500 ǀ 0.5490, 0.2000 ǀ 0.4510)	(0.5000 ǀ 0.8700, 0.4500 ǀ 0.1300)
Super-capacitors	(0.2813 ǀ 0.4880, 0.6756 ǀ 0.5120)	(0.3500 ǀ 0.4900, 0.6000 ǀ 0.5100)	(0.1009 ǀ 0.4830, 0.7983 ǀ 0.5170)	(0.0001 ǀ 0.7200, 0.9886 ǀ 0.2800)	(0.1773 ǀ 0.5470, 0.6455 ǀ 0.4530)	(0.0090 ǀ 0.3550, 0.9730 ǀ 0.6450)	(0.0255 ǀ 0.6800, 0.8298 ǀ 0.3200)	(0.3500 ǀ 0.7530, 0.6000 ǀ 0.2470)	(0.5000 ǀ 0.5400, 0.4500 ǀ 0.4600)
SMES	(0.2979 ǀ 0.3300, 0.6856 ǀ 0.6700)	(0.3500 ǀ 0.2700, 0.6000 ǀ 0.7300)	(0.2017 ǀ 0.1700, 0.6974 ǀ 0.8300)	(0.0004 ǀ 0.5510, 0.9962 ǀ 0.4490)	(0.0886 ǀ 0.4230, 0.8671 ǀ 0.5770)	(0.0180 ǀ 0.8600, 0.9730 ǀ 0.1400)	(0.0851 ǀ 0.5850, 0.1488 ǀ 0.4150)	(0.9000 ǀ 0.8000, 0.1000 ǀ 0.2000)	(0.5000 ǀ 0.7300, 0.4500 ǀ 0.2700)
Thermal (TES)	(0.0463 ǀ 0.5550, 0.9404 ǀ 0.4450)	(0.7500 ǀ 0.5550, 0.2000 ǀ 0.4450)	(0.0504 ǀ 0.1410, 0.8487 ǀ 0.8590)	(0.0228 ǀ 0.4590, 0.9545 ǀ 0.5410)	(0.0004 ǀ 0.3300, 0.9911 ǀ 0.6700)	(0.0090 ǀ 0.2750, 0.9641 ǀ 0.7250)	(0.0003 ǀ 0.7800, 0.9889 ǀ 0.2200)	(0.3500 ǀ 0.3430, 0.6000 ǀ 0.6570)	(0.5000 ǀ 0.3070, 0.4500 ǀ 0.6930)

Table A15. Decision basic data of Expert 9.

Technologies	Energy Efficiency (%)	Response Time	Lifetime (Years)	Energy Density Wh/kg	Self-Discharge Losses (%/Day)	Power Capital Cost (USD/kw)	Energy Capital Cost (USD/kwh)	Environmental Dimension	Social Acceptance
PHS	(65, 80)	Medium	(30, 60)	(0.5, 1.5)	(0.0001, 0.0001)	(600, 2000)	(5, 100)	Very high	Very high
CAES	(41, 75)	Long	(20, 40)	(30, 60)	(0.0001, 0.0001)	(400, 800)	(50, 150)	Very high	Very high
FES	(85, 90)	Medium	(15, 20)	(10, 30)	(20, 100)	(250, 350)	(1000, 5000)	Very high	Very high
Lead–acid	(75, 80)	Very short	(3, 12)	(30, 50)	(0.1, 0.3)	(300, 600)	(150, 500)	Very high	Medium
Li-ion	(65, 78)	Very short	(5, 15)	(75, 250)	(0.1, 0.3)	(1200, 4000)	(600, 2500)	Low	High
Hydrogen	(35, 40)	Medium	(5, 20)	(800, 1000)	(0.5, 2)	(500, 10,000)	(2, 15)	High	Medium
Super-capacitors	(85, 98)	Short	(10, 20)	(0.1, 15)	(20, 40)	(100, 300)	(300, 2000)	Low	Medium
SMES	(90, 95)	Short	(20, 30)	(0.5, 5)	(10, 15)	(200, 300)	(1000, 10,000)	Very high	Medium
Thermal (TES)	(14, 18)	Long	(5, 15)	(30, 60)	(0.05, 1)	(100, 400)	(3, 130)	Low	Medium

Table A16. Initial decision matrix of Expert 9.

Technologies	Energy Efficiency (%)	Response Time	Lifetime (Years)	Energy Density (Wh/kg)	Self-Discharge Losses (%/Day)	Power Capital Cost (USD/kw)	Energy Capital Cost (USD/kwh)	Environmental Dimension	Social Acceptance
PHS	(0.2133 ǀ 0.5000, 0.7375 ǀ 0.5000)	(0.5000 ǀ 0.4670, 0.4500 ǀ 0.5330)	(0.3000 ǀ 0.5510, 0.4001 ǀ 0.4490)	(0.0004 ǀ 0.6700, 0.9989 ǀ 0.3300)	(0.0000 ǀ 0.7000, 1.0000 ǀ 0.3000)	(0.0539 ǀ 0.4300, 0.8203 ǀ 0.5700)	(0.0004 ǀ 0.7570, 0.9915 ǀ 0.2430)	(0.9000 ǀ 0.6670, 0.1000 ǀ 0.3330)	(0.9000 ǀ 0.4500, 0.1000 ǀ 0.5500)
CAES	(0.1345 ǀ 0.6500, 0.7539 ǀ 0.3500)	(0.7500 ǀ 0.6700, 0.2000 ǀ 0.3300)	(0.2000 ǀ 0.6700, 0.6001 ǀ 0.3300)	(0.0229 ǀ 0.4880, 0.9543 ǀ 0.5120)	(0.0000 ǀ 0.5320, 1.0000 ǀ 0.4680)	(0.0359 ǀ 0.6250, 0.9281 ǀ 0.3750)	(0.0043 ǀ 0.6100, 0.9872 ǀ 0.3900)	(0.9000 ǀ 0.4610, 0.1000 ǀ 0.5390)	(0.9000 ǀ 0.6400, 0.1000 ǀ 0.3600)
FES	(0.2789 ǀ 0.4300, 0.7047 ǀ 0.5700)	(0.5000 ǀ 0.8700, 0.4500 ǀ 0.1300)	(0.1500 ǀ 0.8700, 0.8000 ǀ 0.1300)	(0.0076 ǀ 0.7300, 0.9771 ǀ 0.2700)	(0.1773 ǀ 0.6930, 0.1137 ǀ 0.3070)	(0.0225 ǀ 0.5420, 0.9686 ǀ 0.4580)	(0.0851 ǀ 0.6930, 0.5744 ǀ 0.3070)	(0.9000 ǀ 0.5440, 0.1000 ǀ 0.4560)	(0.9000 ǀ 0.4200, 0.1000 ǀ 0.5800)
Lead–acid	(0.2461 ǀ 0.7820, 0.7375 ǀ 0.2180)	(0.1000 ǀ 0.5400, 0.9000 ǀ 0.4600)	(0.0300 ǀ 0.7570, 0.8800 ǀ 0.2430)	(0.0229 ǀ 0.2800, 0.9619 ǀ 0.7200)	(0.0009 ǀ 0.2390, 0.9973 ǀ 0.7610)	(0.0270 ǀ 0.4670, 0.9461 ǀ 0.5330)	(0.0128 ǀ 0.2390, 0.9574 ǀ 0.7610)	(0.9000 ǀ 0.2100, 0.1000 ǀ 0.7900)	(0.5000 ǀ 0.4670, 0.4500 ǀ 0.5330)
Li-ion	(0.2133 ǀ 0.4520, 0.7441 ǀ 0.5480)	(0.1000 ǀ 0.6930, 0.9000 ǀ 0.3070)	(0.0500 ǀ 0.6100, 0.8500 ǀ 0.3900)	(0.0572 ǀ 0.6100, 0.8095 ǀ 0.3900)	(0.0009 ǀ 0.5600, 0.9973 ǀ 0.4400)	(0.1078 ǀ 0.5600, 0.6406 ǀ 0.4400)	(0.0511 ǀ 0.6000, 0.7872 ǀ 0.4000)	(0.3500 ǀ 0.4670, 0.6000 ǀ 0.5330)	(0.7500 ǀ 0.6670, 0.2000 ǀ 0.3330)
Hydrogen	(0.1148 ǀ 0.4560, 0.8688 ǀ 0.5440)	(0.5000 ǀ 0.2390, 0.4500 ǀ 0.7610)	(0.0500 ǀ 0.3100, 0.8000 ǀ 0.6900)	(0.6097 ǀ 0.5600, 0.2379 ǀ 0.4400)	(0.0044 ǀ 0.5440, 0.9823 ǀ 0.4560)	(0.0449 ǀ 0.5490, 0.1016 ǀ 0.4510)	(0.0002 ǀ 0.5030, 0.9987 ǀ 0.4970)	(0.7500 ǀ 0.4900, 0.2000 ǀ 0.5100)	(0.5000 ǀ 0.8700, 0.4500 ǀ 0.1300)
Super-capacitors	(0.2789 ǀ 0.6460, 0.6785 ǀ 0.3540)	(0.3500 ǀ 0.3180, 0.6000 ǀ 0.6820)	(0.1000 ǀ 0.2700, 0.8000 ǀ 0.7300)	(0.0001 ǀ 0.5490, 0.9886 ǀ 0.4510)	(0.1773 ǀ 0.8400, 0.6455 ǀ 0.1600)	(0.0090 ǀ 0.8300, 0.9730 ǀ 0.1700)	(0.0255 ǀ 0.8200, 0.8298 ǀ 0.1800)	(0.3500 ǀ 0.8300, 0.6000 ǀ 0.1700)	(0.5000 ǀ 0.5400, 0.4500 ǀ 0.4600)
SMES	(0.2953 ǀ 0.5000, 0.6883 ǀ 0.5000)	(0.3500 ǀ 0.4150, 0.6000 ǀ 0.5850)	(0.2000 ǀ 0.2400, 0.7000 ǀ 0.7600)	(0.0004 ǀ 0.8300, 0.9962 ǀ 0.1700)	(0.0886 ǀ 0.5420, 0.8671 ǀ 0.4580)	(0.0180 ǀ 0.8820, 0.9730 ǀ 0.1180)	(0.0851 ǀ 0.4220, 0.1488 ǀ 0.5780)	(0.9000 ǀ 0.8500, 0.1000 ǀ 0.1500)	(0.5000 ǀ 0.7000, 0.4500 ǀ 0.3000)
Thermal (TES)	(0.0459 ǀ 0.2190, 0.9409 ǀ 0.7810)	(0.7500 ǀ 0.4500, 0.2000 ǀ 0.5500)	(0.0500 ǀ 0.1700, 0.8500 ǀ 0.8300)	(0.0229 ǀ 0.5000, 0.9543 ǀ 0.5000)	(0.0004 ǀ 0.4670, 0.9911 ǀ 0.5330)	(0.0090 ǀ 0.3050, 0.9641 ǀ 0.6950)	(0.0003 ǀ 0.5990, 0.9889 ǀ 0.4010)	(0.3500 ǀ 0.3400, 0.6000 ǀ 0.6600)	(0.5000 ǀ 0.3450, 0.4500 ǀ 0.6550)

Table A17. Decision basic data of Expert 10.

Technologies	Energy Efficiency (%)	Response Time	Lifetime (Years)	Energy Density Wh/kg	Self-Discharge Losses (%/Day)	Power Capital Cost (USD/kw)	Energy Capital Cost (USD/kwh)	Environmental Dimension	Social Acceptance
PHS	(65, 75)	Medium	(30, 60)	(0.5, 1.5)	(0.0001, 0.0001)	(600, 2000)	(5, 100)	Very high	Very high
CAES	(41, 75)	Long	(20, 40)	(30, 60)	(0.0001, 0.0001)	(400, 800)	(50, 150)	Very high	Very high
FES	(80, 90)	Medium	(15, 20)	(5, 130)	(20, 100)	(250, 350)	(1000, 5000)	Very high	Very high
Lead–acid	(75, 80)	Very short	(3, 12)	(30, 50)	(0.1, 0.3)	(300, 600)	(150, 500)	Very high	Medium
Li-ion	(65, 75)	Very short	(5, 15)	(75, 200)	(0.1, 0.3)	(1200, 4000)	(600, 2500)	Low	High
Hydrogen	(35, 40)	Medium	(5, 20)	(800, 1000)	(0.5, 2)	(500, 10,000)	(2, 15)	High	Medium
Super-capacitors	(85, 98)	Short	(10, 20)	(0.1, 15)	(20, 40)	(100, 300)	(300, 2000)	Low	Medium
SMES	(90, 95)	Short	(20, 30)	(0.5, 5)	(10, 15)	(200, 300)	(1000, 10,000)	Very high	Medium
Thermal (TES)	(14, 18)	Long	(5, 15)	(30, 60)	(0.05, 1)	(100, 400)	(3, 130)	Low	Medium

Table A18. Initial decision matrix of Expert 10.

Technologies	Energy Efficiency (%)	Response Time	Lifetime (Years)	Energy Density (Wh/kg)	Self-Discharge Losses (%/Day)	Power Capital Cost (USD/kw)	Energy Capital Cost (USD/kwh)	Environmental Dimension	Social Acceptance
PHS	(0.2157 | 0.5400, 0.7511 | 0.4600)	(0.5000 | 0.4500, 0.4500 | 0.5500)	(0.3000 | 0.6930, 0.4001 | 0.3070)	(0.0004 | 0.4880, 0.9989 | 0.5120)	(0.0000 | 0.8700, 1.0000 | 0.1300)	(0.0539 | 0.6400, 0.8203 | 0.3600)	(0.0004 | 0.6400, 0.9915 | 0.3600)	(0.9000 | 0.7200, 0.1000 | 0.2800)	(0.9000 | 0.3200, 0.1000 | 0.6800)
CAES	(0.1360 | 0.3940, 0.7511 | 0.6060)	(0.7500 | 0.4900, 0.2000 | 0.5100)	(0.2000 | 0.2700, 0.6001 | 0.7300)	(0.0229 | 0.3300, 0.9542 | 0.6700)	(0.0000 | 0.5400, 1.0000 | 0.4600)	(0.0359 | 0.3300, 0.9281 | 0.6700)	(0.0043 | 0.5630, 0.9872 | 0.4370)	(0.9000 | 0.5630, 0.1000 | 0.4370)	(0.9000 | 0.4800, 0.1000 | 0.5200)
FES	(0.2654 | 0.3200, 0.7014 | 0.6800)	(0.5000 | 0.7200, 0.4500 | 0.2800)	(0.1500 | 0.7200, 0.8000 | 0.2800)	(0.0038 | 0.5470, 0.9007 | 0.4530)	(0.1773 | 0.7340, 0.1137 | 0.2660)	(0.0225 | 0.5470, 0.9686 | 0.4530)	(0.0851 | 0.3460, 0.5744 | 0.6540)	(0.9000 | 0.2390, 0.1000 | 0.7610)	(0.9000 | 0.6250, 0.1000 | 0.3750)
Lead–acid	(0.2489 | 0.4800, 0.7346 | 0.5200)	(0.1000 | 0.4800, 0.9000 | 0.5200)	(0.0300 | 0.5510, 0.8800 | 0.4490)	(0.0229 | 0.5510, 0.9618 | 0.4490)	(0.0009 | 0.7200, 0.9973 | 0.2800)	(0.0270 | 0.4230, 0.9461 | 0.5770)	(0.0128 | 0.6400, 0.9574 | 0.3600)	(0.9000 | 0.6400, 0.1000 | 0.3600)	(0.5000 | 0.4700, 0.4500 | 0.5300)
Li-ion	(0.2157 | 0.2700, 0.7511 | 0.7300)	(0.1000 | 0.2390, 0.9000 | 0.7610)	(0.0500 | 0.3200, 0.8500 | 0.6800)	(0.0573 | 0.7800, 0.8473 | 0.2200)	(0.0009 | 0.6930, 0.9973 | 0.3070)	(0.1078 | 0.3300, 0.6406 | 0.6700)	(0.0511 | 0.4880, 0.7872 | 0.5120)	(0.3500 | 0.5600, 0.6000 | 0.4400)	(0.7500 | 0.6700, 0.2000 | 0.3300)
Hydrogen	(0.1161 | 0.3460, 0.8673 | 0.6540)	(0.5000 | 0.3460, 0.4500 | 0.6540)	(0.0500 | 0.4800, 0.8000 | 0.5200)	(0.6108 | 0.4500, 0.2364 | 0.5500)	(0.0044 | 0.2390, 0.9823 | 0.7610)	(0.0449 | 0.2000, 0.1016 | 0.8000)	(0.0002 | 0.3300, 0.9987 | 0.6700)	(0.7500 | 0.5490, 0.2000 | 0.4510)	(0.5000 | 0.6930, 0.4500 | 0.3070)
Super-capacitors	(0.2820 | 0.6400, 0.6748 | 0.3600)	(0.3500 | 0.3200, 0.6000 | 0.6800)	(0.1000 | 0.6250, 0.8000 | 0.3750)	(0.0001 | 0.3570, 0.9885 | 0.6430)	(0.1773 | 0.3570, 0.6455 | 0.6430)	(0.0090 | 0.5600, 0.9730 | 0.4400)	(0.0255 | 0.5400, 0.8298 | 0.4600)	(0.3500 | 0.8300, 0.6000 | 0.1700)	(0.5000 | 0.5700, 0.4500 | 0.4300)
SMES	(0.2986 | 0.4600, 0.6848 | 0.5400)	(0.3500 | 0.1900, 0.6000 | 0.8100)	(0.2000 | 0.5420, 0.7000 | 0.4580)	(0.0004 | 0.2890, 0.9962 | 0.7110)	(0.0886 | 0.2890, 0.8671 | 0.7110)	(0.0180 | 0.5490, 0.9730 | 0.4510)	(0.0851 | 0.4230, 0.1488 | 0.5770)	(0.9000 | 0.8590, 0.1000 | 0.1410)	(0.5000 | 0.6420, 0.4500 | 0.3580)
Thermal (TES)	(0.0465 | 0.6340, 0.9403 | 0.3660)	(0.7500 | 0.4600, 0.2000 | 0.5400)	(0.0500 | 0.4670, 0.8500 | 0.5330)	(0.0229 | 0.3070, 0.9542 | 0.6930)	(0.0004 | 0.2310, 0.9911 | 0.7690)	(0.0090 | 0.4900, 0.9641 | 0.5100)	(0.0003 | 0.3300, 0.9889 | 0.6700)	(0.3500 | 0.4300, 0.6000 | 0.5700)	(0.5000 | 0.3700, 0.4500 | 0.6300)

Appendix B

The average value matrices for each expert are detailed in Table A19 in Appendix B.

Table A19. The average value matrices for each expert.

Experts	Energy Efficiency (%)	Response Time	Lifetime (Years)	Energy Density Wh/kg	Self-Discharge Losses (%/Day)	Power Capital Cost (USD/kw)	Energy Capital Cost (USD/kwh)	Environmental Dimension	Social Acceptance
Expert 1	7.96590	9.27802	8.99335	8.73240	9.00472	9.94291	8.26127	11.55204	6.98992
Expert 2	7.88640	9.19959	6.41355	7.90159	9.69595	8.88834	7.26663	9.10935	7.42257
Expert 3	5.94775	9.32811	5.94226	8.78331	8.94545	9.94798	8.04049	11.67451	6.41061
Expert 4	7.68124	11.05909	6.97667	8.13294	10.96102	9.33751	8.26127	11.55204	8.37422
Expert 5	5.34921	10.67288	7.62917	9.38572	9.30615	6.78349	9.58478	11.08139	5.63756
Expert 6	7.46296	9.65876	5.83586	9.77153	7.59372	6.46601	6.49173	10.43268	7.03724
Expert 7	7.41159	7.36556	8.28056	11.98176	8.53986	9.47546	8.26805	9.58418	6.50334
Expert 8	3.69444	8.48522	9.58655	7.36255	8.07166	9.96647	8.32638	10.94746	7.88742
Expert 9	7.27922	9.41622	9.91031	9.09937	9.50954	8.92427	8.50127	11.27877	7.04607
Expert 10	5.47968	10.61353	6.43756	9.57527	11.49334	6.19716	7.00807	11.09520	6.82443

Appendix C

The weighted initial decision matrix is shown in Table A20 in Appendix C.

Table A20. The weighted initial decision matrix.

Technologies	Energy Efficiency (%)	Response Time	Lifetime (Years)	Energy Density (Wh/kg)	Self-Discharge Losses (%/Day)	Power Capital Cost (USD/kw)	Energy Capital Cost (USD/kwh)	Environmental Dimension	Social Acceptance
PHS	(0.2197 | 0.0051, 0.7472 | 0.0001)	(0.5000 | 0.0005, 0.4500 | 0.0015)	(0.3010 | 0.0155, 0.3981 | 0.0000)	(0.0004 | 0.0064, 0.9989 | 0.0000)	(0.0000 | 0.0064, 1.0000 | 0.0000)	(0.0545 | 0.0012, 0.7976 | 0.0003)	(0.0004 | 0.0171, 0.9888 | 0.0000)	(0.9000 | 0.0109, 0.1000 | 0.0000)	(0.9000 | 0.0005, 0.1000 | 0.0012)
CAES	(0.1355 | 0.0010, 0.7522 | 0.0008)	(0.7500 | 0.0053, 0.2000 | 0.0001)	(0.2006 | 0.0011, 0.5987 | 0.0004)	(0.0229 | 0.0005, 0.9543 | 0.0009)	(0.0000 | 0.0027, 1.0000 | 0.0001)	(0.0357 | 0.0053, 0.9286 | 0.0000)	(0.0043 | 0.0018, 0.9872 | 0.0004)	(0.9000 | 0.0002, 0.1000 | 0.0017)	(0.9000 | 0.0060, 0.1000 | 0.0001)
FES	(0.2704 | 0.0011, 0.7042 | 0.0002)	(0.5000 | 0.0053, 0.4500 | 0.0000)	(0.1505 | 0.0006, 0.7994 | 0.0003)	(0.0061 | 0.0008, 0.9524 | 0.0001)	(0.1773 | 0.0004, 0.1137 | 0.0005)	(0.0223 | 0.0005, 0.9688 | 0.0012)	(0.0851 | 0.0086, 0.5744 | 0.0000)	(0.9000 | 0.0002, 0.1000 | 0.0027)	(0.9000 | 0.0011, 0.1000 | 0.0006)
Lead–acid	(0.2462 | 0.0023, 0.7357 | 0.0001)	(0.1000 | 0.0079, 0.9000 | 0.0000)	(0.0301 | 0.0038, 0.8796 | 0.0001)	(0.0229 | 0.0009, 0.9619 | 0.0003)	(0.0009 | 0.0027, 0.9973 | 0.0001)	(0.0268 | 0.0023, 0.9464 | 0.0002)	(0.0128 | 0.0000, 0.9574 | 0.0052)	(0.9000 | 0.0000, 0.1000 | 0.0044)	(0.5000 | 0.0003, 0.4500 | 0.0024)
Li-ion	(0.2148 | 0.0003, 0.7482 | 0.0009)	(0.1000 | 0.0015, 0.9000 | 0.0002)	(0.0502 | 0.0038, 0.8495 | 0.0001)	(0.0571 | 0.0002, 0.8133 | 0.0009)	(0.0009 | 0.0005, 0.9973 | 0.0009)	(0.1072 | 0.0001, 0.6428 | 0.0027)	(0.0511 | 0.0051, 0.7872 | 0.0001)	(0.3500 | 0.0009, 0.6000 | 0.0003)	(0.7500 | 0.0013, 0.2000 | 0.0002)
Hydrogen	(0.1157 | 0.0004, 0.8679 | 0.0012)	(0.5000 | 0.0001, 0.4500 | 0.0021)	(0.0502 | 0.0002, 0.8240 | 0.0019)	(0.6092 | 0.0003, 0.2385 | 0.0016)	(0.0044 | 0.0002, 0.9823 | 0.0014)	(0.0447 | 0.0034, 0.1060 | 0.0001)	(0.0002 | 0.0017, 0.9987 | 0.0004)	(0.7500 | 0.0013, 0.2000 | 0.0007)	(0.5000 | 0.0355, 0.4500 | 0.0000)
Super-capacitors	(0.2809 | 0.0130, 0.6762 | 0.0000)	(0.3500 | 0.0001, 0.6000 | 0.0009)	(0.1003 | 0.0012, 0.7944 | 0.0002)	(0.0001 | 0.0038, 0.9886 | 0.0001)	(0.1773 | 0.0010, 0.6455 | 0.0001)	(0.0089 | 0.0009, 0.9732 | 0.0002)	(0.0255 | 0.0145, 0.8298 | 0.0000)	(0.3500 | 0.0514, 0.6000 | 0.0000)	(0.5000 | 0.0030, 0.4500 | 0.0001)
SMES	(0.2974 | 0.0015, 0.6861 | 0.0002)	(0.3500 | 0.0000, 0.6000 | 0.0051)	(0.2006 | 0.0000, 0.6991 | 0.0045)	(0.0004 | 0.0005, 0.9962 | 0.0003)	(0.0886 | 0.0012, 0.8671 | 0.0002)	(0.0179 | 0.0815, 0.9732 | 0.0000)	(0.0851 | 0.0039, 0.1489 | 0.0001)	(0.9000 | 0.0874, 0.1000 | 0.0000)	(0.5000 | 0.0386, 0.4500 | 0.0000)
Thermal (TES)	(0.0463 | 0.0001, 0.9405 | 0.0032)	(0.7500 | 0.0011, 0.2000 | 0.0003)	(0.0502 | 0.0000, 0.8495 | 0.0010)	(0.0229 | 0.0002, 0.9543 | 0.0016)	(0.0004 | 0.0000, 0.9911 | 0.0064)	(0.0089 | 0.0000, 0.9643 | 0.0041)	(0.0003 | 0.0099, 0.9889 | 0.0000)	(0.3500 | 0.0003, 0.6000 | 0.0016)	(0.5000 | 0.0002, 0.4500 | 0.0019)

Appendix D

The expert's evaluation information in Scenario 1 to Scenario 3 are shown in Table A21 to Table A23 in Appendix D.

Table A21. The expert's evaluation information in Scenario 1.

Experts	Energy Efficiency (%)	Response Time	Lifetime (Years)	Energy Density (Wh/kg)	Self-Discharge Losses (%/Day)	Power Capital Cost (USD/kw)	Energy Capital Cost (USD/kwh)	Environmental Dimension	Social Acceptance
Expert 1	(55, 80)	Short	(12, 35)	(40, 70)	(5, 15)	(100, 700)	(100, 300)	Low	Very high
Expert 2	(55, 75)	Short	(20, 40)	(20, 105)	(1, 10)	(300, 1000)	(200, 650)	Low	Medium
Expert 3	(50, 85)	Very short	(15, 30)	(30, 80)	(0.5, 12)	(300, 600)	(600, 5000)	Medium	Very high
Expert 4	(60, 80)	Medium	(20, 30)	(15, 60)	(0.2, 5)	(150, 600)	(250, 1000)	Low	High
Expert 5	(75, 82)	Very short	(10, 50)	(25, 120)	(2, 25)	(100, 500)	(300, 550)	Very low	High
Expert 6	(44, 85)	Short	(20, 60)	(25, 60)	(2, 50)	(200, 600)	(400, 1000)	Low	Medium
Expert 7	(55, 90)	Very short	(40, 50)	(15, 80)	(0.1, 15)	(250, 500)	(1000, 10,000)	Very low	High
Expert 8	(62, 90)	Short	(20, 35)	(40, 85)	(10, 25)	(600, 1000)	(250, 1000)	Medium	High
Expert 9	(40, 80)	Very short	(10, 30)	(35, 80)	(0.5, 20)	(500, 800)	(350, 1000)	Medium	High
Expert 10	(70, 80)	Short	(10, 30)	(45, 65)	(55, 85)	(120, 650)	(500, 800)	Very low	Very high

Table A22. The expert's evaluation information in Scenario 2.

Experts	Energy Efficiency (%)	Response Time	Lifetime (Years)	Energy Density (Wh/kg)	Self-Discharge Losses (%/Day)	Power Capital Cost (USD/kw)	Energy Capital Cost (USD/kwh)	Environmental Dimension	Social Acceptance
Expert 1	(65, 80)	Very short	(15, 36)	(50, 80)	(5, 15)	(300, 700)	(150, 300)	Low	Very high
Expert 2	(65, 75)	Short	(25, 40)	(40, 105)	(2, 10)	(400, 1000)	(250, 650)	Low	Medium
Expert 3	(60, 85)	Very short	(18, 30)	(50, 80)	(0.5, 20)	(350, 650)	(800, 5000)	Medium	Very high
Expert 4	(70, 80)	Medium	(20, 30)	(35, 60)	(0.2, 10)	(250, 700)	(250, 1000)	Low	High
Expert 5	(75, 90)	Very short	(20, 50)	(45, 120)	(5, 25)	(150, 600)	(400, 550)	Very low	High
Expert 6	(60, 85)	Short	(35, 60)	(35, 60)	(8, 55)	(300, 600)	(400, 1000)	Low	Medium
Expert 7	(70, 90)	Very short	(40, 55)	(55, 88)	(0.1, 20)	(350, 550)	(1000, 10,000)	Very low	High
Expert 8	(66, 90)	Short	(20, 45)	(40, 95)	(10, 25)	(650, 1100)	(350, 1100)	Medium	Medium
Expert 9	(60, 80)	Very short	(10, 30)	(40, 82)	(0.5, 25)	(500, 850)	(450, 1100)	Medium	High
Expert 10	(77, 80)	Short	(25, 30)	(50, 70)	(60, 85)	(120, 750)	(500, 850)	Very low	Very high

Table A23. The expert's evaluation information in Scenario 3.

Experts	Energy Efficiency (%)	Response Time	Lifetime (Years)	Energy Density (Wh/kg)	Self-Discharge Losses (%/day)	Power Capital Cost (USD/kw)	Energy Capital Cost (USD/kwh)	Environmental Dimension	Social Acceptance
Expert 1	(50, 70)	Short	(8, 30)	(40, 65)	(1, 5)	(100, 300)	(50, 200)	Low	Very high
Expert 2	(50, 70)	Medium	(15, 20)	(10, 100)	(0.5, 5)	(300, 800)	(200, 350)	Very low	High
Expert 3	(45, 80)	Very short	(12, 30)	(15, 75)	(0.1, 8)	(100, 500)	(500, 3000)	Very low	Very high
Expert 4	(60, 80)	Medium	(12, 35)	(15, 45)	(0.1, 5)	(150, 450)	(150, 400)	Low	High
Expert 5	(70, 75)	Medium	(12, 40)	(25, 110)	(0.5, 10)	(50, 250)	(300, 400)	Very low	Medium
Expert 6	(40, 75)	Short	(25, 50)	(20, 30)	(0.1, 25)	(200, 300)	(100, 1000)	Low	High
Expert 7	(50, 85)	Medium	(15, 50)	(10, 50)	(0.1, 10)	(200, 400)	(1000, 5000)	Very low	High
Expert 8	(55, 80)	Medium	(10, 30)	(45, 80)	(9, 15)	(500, 1000)	(150, 600)	Low	Medium
Expert 9	(35, 65)	Very short	(5, 15)	(30, 80)	(0.5, 10)	(400, 600)	(350, 600)	Medium	High
Expert 10	(60, 70)	Short	(10, 35)	(45, 65)	(25, 45)	(80, 300)	(200, 600)	Very low	Very high

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