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Assessing technology portfolios of clean energy-driven desalination-irrigation systems with interval-valued intuitionistic fuzzy sets

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ABSTRACT

In arid and semi-arid regions, there exist great potential for supplementing irrigation water with brackish water desalinated by clean energies. Determining technology portfolio is essential for the establishment of clean energy-driven desalination-irrigation (CEDI) systems, requiring multi-criteria group decision-making. Unfortunately, few existing methods were capable of assessing such a complex problem that involves multiple technologies and uncertainties. During multi-criteria group decision-making, uncertainty arising from linguistic information and varying confidence in estimation is usually available as interval-valued intuitionistic fuzzy sets (IVIFSs). Previous studies relied on the direct provision of IVIFSs by experts, which made them inapplicable in real-world problems because experts' understanding over IVIFSs might be limited and inconsistent. Therefore, an easy-to-operate method for collection and conversion of IVIFSs was proposed in this study to avoid misunderstanding and facilitate realistic reflection of expert judgements. Duplex rating sets (DRSs) were proposed to express uncertain estimates and the associated confidence levels, and transformation equations were established to convert DRSs into IVIFSs. Based on the introduction of DRSs and transformation equations, an entropy-weighted TOPSIS approach with IVIFSs information was then developed. The developed method was then applied to northwest China for supporting the assessment of CEDI technology portfolios. The most desirable portfolio was screened out under the criteria of agriculture, ecology, economy, and system performance. Moreover, results of sensitivity analysis showed that the selected portfolio would perform the best in twelve of the total twenty scenarios. Without loss of generality, the developed method is also applicable for other decision-making problems involving multiple criteria, stakeholders and uncertainties.

1. Introduction

Arid regions cover almost 40% of the world's population and 44% of the world's cultivated lands [1]. Approximately half of the world population in 2030 have to live in high water-stress areas under future climate scenarios [2]. The ability to continue producing food in arid regions is one of the keys to feeding 9 billion people by 2050. Arid regions in Northwest China account for over one fourth of China's total territory but only about 8% of the country's total runoff [3]. While the lack of fresh water has greatly hindered food production in this region, brackish water is abundant in this region and could possibly be desalinated for irrigation use [4]. At present, most of the desalination facilities for industry use are driven by traditional fuels, which lead to the increase of CO_2 emissions and greenhouse effects, and finally the decrease of fresh water [5]. Desalination powered by traditional fuels is also an expensive option for irrigation, which impeded its application in underdeveloped areas such as northwestern provinces of China. Previous studies [6–10] showed the great potential of renewable energy powered desalinated water for irrigation(e.g., solar driven capacitive deionization is found economically feasible for irrigation in farm scales; simulation result tells the renewable energy desalination can offer an affordable supply for irrigation supply as conventional water price increase). Arid regions normally have plentiful renewable energy sources, such as wind and solar energy, which provides an opportunity for

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brackish water desalination and irrigation powered by clean energy. As the first step of system design, technology portfolios lay a foundation for subsequent process design and control. Therefore, screening of appropriate technology portfolios is of utmost significance for successful establishment of clean energy driven desalination-irrigation (CEDI) systems.

By making good use of local resources, CEDI systems have multifaceted benefits such as water shortage alleviation, carbon emission reduction, and food production enhancement. Clean energy is used to generate electricity which drives desalination and irrigation. This food-energy-water nexus approach contains three core technology links, including power generation, desalination and irrigation. Different options are available for each technology link, and their combinations form different technology portfolios that have varied influences over economy, environment and society. In the past, there have been a number of studies related to the assessment of one or more links in CEDI systems from the perspectives of economic viability and/or technical soundness. In studies related to only one technology link of CDEI system, tools like benefit - cost analysis [11], life cycle analysis [12], weighing and ranking method [13], controlled experiment [14,15] have been used in comparison of different technology options. In addition, there have also been a number of studies involving two links of CEDIs. For example, some studies compared desalination technologies driven by clean energies [16,17]; some studies focused on investigating economic feasibility and environmental impacts of irrigaiton with desalinated water [18,19]; and some studies assessed the feasibility and performance of irrigation driven by clean energies [20–22]. Compared to the selection of one or two technologies, the determination of a technology portfolio for the complete power generation-desalination-irrigation process within a CEDI system is much more complex. It is nearly impossible for an individual decision maker to thoroughly consider all the aspects of a problem, calling for advanced approaches that can communicate the opinions given by a group of experts with varied expertise and interests under multiple criteria into the assessment process [23–25].

Multi-criteria decision-making (MCDM) emerged in the 1950s [26]. It is a set of techniques to comprehensively evaluate the integrated performance of alternatives using multiple criteria [27,28]. Deterministic MCDM methods include multi-attribute utility theory (MAUT) methods [29], outranking relation methods (e.g., ELECTRE [30] and PROMETHEE [31]), and methods based on ideal solution comparison (e.g., TOPSIS [32,33] and VIKOR [34,35]). Among these methods, TOPSIS has attracted much attention for its ability to locate the best alternative that is the closest to the ideal point [26]. TOPSIS ranks all the alternatives by weighted distance measures, thus weight determination plays an important role in obtaining a reasonable solution [36]. Weight determination can be divided into subjective methods and objective methods. Subjective weights are predefined by the experts/-stakeholders: sometimes weights could be given as exact numbers; sometimes weights could be calculated by pair-wise comparison of relative importance (e.g., AHP) [37]; sometimes weights could be determined by the precedence order of criteria [38]. More scholars focused on objective weight determination methods such as entropy-weighted method [39–41], in which weight determination does not rely on experts' opinions. Entropy-weighted method assigns weights to criteria/groups according to the information entropy, which quantify the information contained in different criteria/groups [39]. Furthermore, many studies have also focused on multi-criteria group decision-making (MCGDM) processes, which extended MCDM by emphasizing the combination of different experts' opinions [42,43]. Weight determination for experts is crucial to aggregate different experts' estimates and achieve a reasonable decision-making in MCGDM problems. Previous studies [41,44,45] implicated entropy-weighted method is also applicable for objective determination of experts weights.

Although substantial deterministic MCGDM approaches have managed to objectively determine weights for criteria and experts, they could not deal with multiple uncertainties existing in the estimates [46–49]. The estimates of experts may be linguistic [50] and inexact [51]. Sometimes they may be available as intervals with only lower and upper bounds being specified [52]. In addition, experts are not always confident of their estimates because their knowledge and experiences of some criteria/alternatives may be limited [53]. For evaluation of different alternatives according to the same criteria or evaluation of the same alternative according to different criteria, different experts are involved and their hesitation/confidence levels varied. In fact, interval-valued intuitionistic fuzzy sets (IVIFSs) that were proposed by Atanassov and Gargov [54] by combining intuitionistic fuzzy sets (IFSs) [55] and interval-valued fuzzy sets (IVFSs) [56] could express such uncertainties. IVIFSs can express the support, opposition, and neutrality (hesitation) of experts as membership intervals, non-membership intervals, and intuitionistic intervals, respectively. IVIFSs have been successfully applied to the areas of supply and investment decision-making [57–59]. For tackling MCGDM problems with IVIFSs information, some researchers explored how to extend the classic MCDM methods [60–62], and the others established novel approaches based on the measures of IVIFSs [63].

Previous studies focused on how to address MCGDM with directly given estimates in the format of IVIFSs, data collection for experts' estimates and corresponding hesitation degrees had not attracted attention yet. However, in real-world problems as experts' understanding over IVIFSs may be very limited, and directly given IVIFSs information may lead to inaccuracy in data collected. There was a lack of approaches that explored how to capture and translate experts' preference and corresponding hesitation degrees into appropriate IVIFSs without loss of any information. An easy-to-operate method for data collection and conversion of IVIFSs is highly in need to facilitate the expression of expert judgements and avoid misunderstanding in communication. Moreover, to the best of our knowledge, experts' estimates have seldom been expressed as IVIFSs in the evaluation process involving water, energy, food or technologies, let alone in the energy-water-food technology portfolio selection.

Therefore, a concept of duplex rating sets (DRSs) will be proposed in this study to collect information of estimates and corresponding confidence levels. Then transforming equations will be established to convert DRSs information into IVIFSs expressions, including the determination of membership intervals, non-membership intervals, and intuitionistic intervals. In addition, an entropy-weighted TOPSIS framework with IVIFSs information will be proposed to address MCGDM problems. The developed method will be applied to a case study in northwestern China for screening the optimal energy-water-food technology portfolio of CEDI systems. The output of this model will provide the most suitable technology portfolio of CEDI systems, which lay a foundation of subsequent system design, parameter optimization and technology promotion.

This paper is organized as follows. Section 2 developed an entropy-weighted TOPSIS approach with IVIFSs information to address MCGDM problems. Section 3 mainly implements a practical example in northwest China to demonstrate the validity and practicability of this model. Section 4 includes analyses and discussions of the results. Section 5 provides concluding remarks of this research and an outlook for future research.

2. Methodology

This section developed an entropy-weighted TOPSIS approach with IVIFSs information to address MCGDM problems. Some preliminary knowledge about IVIFSs was introduced, and then the steps of the proposed model were illustrated.

2.1. Preliminary of IVIFSs

2.1.1. Definition of IVIFSs

According to Atanassov's definition, an IFSs A defined on X is $A = \{ x,$

$\mu_A(x)| x\in X\}$, where X is a non-empty set called the universe of discourse; $\mu_A(x): X \to [0,1]$ and $\upsilon_A(x): X \to [0,1]$; $0 \le \mu_A(x) + \upsilon_A(x) \le 1$ for all $x\in X$; $\mu_A(x)$, and $\upsilon_A(x)$ are called respectively the membership degree and non-membership degree of x to A. Hesitancy degree or intuitionistic index of x to A is defined as $\pi_A(x) = 1 - \mu_A(x) - \upsilon_A(x)$ for all $x\in X$, $\pi_A(x)\in[0, 1]$. Intuitionistic fuzzy sets enable decision makers to express three attitudes, namely, support($\mu_A(x)$), opposition($\upsilon_A(x)$), and neutrality ($\pi_A(x)$). The membership degree function $\mu_A(x)$ stands for how much the element x belongs to set A. Oppositely, the non-membership degree stands for how much the element x does not belong to the set A. $\pi_A(x)$ stands for an state that is neither membership degree nor non-membership degree, which can depict the hesitant degree (neutrality) of experts in evaluation processes. To illustrate the difference between intuitionistic fuzzy sets and fuzzy sets, Fig. 1 is placed below. It can be seen that the determination of a fuzzy number requires only one parameter ($\mu_A(x)$ or $\upsilon_A(x)$), while an intuitionistic fuzzy number requires two.

In reality, however, it may not be easy to identify exact values for the membership and non-membership degrees of an element to a given set [64]. Thus, Atanassov and Gargov introduced the notion of an interval-valued intuitionistic fuzzy set (IVIFSs), which is characterized by a membership function and a non-membership function, whose values are intervals rather than real numbers. An IVIFS on X is defined by Atanassov and Gargov as: A = $\{x, [\mu_{AL}(x), \mu_{AU}(x)], [\upsilon_{AL}(x), \upsilon_{AU}(x)]| x \in X\}$, where X is a non-empty set called the universe of discourse, for each $x \in X$, $\mu_A(x)$ and $\upsilon_A(x)$ are closed intervals and their lower and upper end points are denoted by $\mu_{AL}(x)$, $\mu_{AU}(x)$, $\upsilon_{AL}(x)$, and $\upsilon_{AU}(x)$, respectively; $0\le\upsilon_{AL}(x)+\mu_{AL}(x)\le1$; $0\le\upsilon_{AU}(x)+ \mu_{AU}(x)\le1$; and $\mu_{AL}(x)$, $\mu_{AU}(x)$, $\upsilon_{AL}(x)$ and $\upsilon_{AU}(x)$ are nonnegative values. For each element x, the intuitionistic interval of $x \in X$ is defined as: $\pi_A(x) = 1-\mu_A(x)- \upsilon_A(x) = [1-\mu_{AU}(x)- \upsilon_{AU}(x), 1-\mu_{AL}(x)- \upsilon_{AL}(x)]$. IVIFSs may suitably describe MCGDM problem in which satisfaction degrees of alternatives on attributes and importance degrees of attributes cannot be expressed with exact numerical values.

In decision-making process, suppose A is a criterion, x is an element of a non-empty universe of X. IVIFSs number $A(x)$ can express a complex membership status of the element x to the criterion A of a decision maker, which uses membership interval, non-membership interval, and intuitionistic interval to denote support, opposition, and neutrality.

2.1.2. Definition and conversion of DRSs

Owing to the different backgrounds of experts, they may have different knowledge levels of IVIFSs. To facilitate the communication of experts and avoid misunderstanding of IVIFSs, duplex rating sets (DRSs) that can be converted to IVIFSs, which can collect information in both alternative performance and hesitant degree, were established. Let X be a non-empty set called the universe of discourse, A duplex rating set $A(x)$ was defined as: $A = \{x,(P_N(x),C_s(x))| x \in X\}$, $P_N(x)$ is called the performance rating of element x, where $P_N(x) = 1,2, \ldots, N$; $C_s(x)$ is called the confidence rating of the performance rating, where $C_s(x) = 1,2, \ldots,S$; N, S are the amounts of total $P_N(x)$ and $C_s(x)$.

DRSs can be useful in collecting both the preference and the confidence degree of decision makers by questionnaires, they may be asked to assess the performance first, and then give the confidence levels of their judgements. To realize the application of DRSs in MCGDM problem, a conversion method from DRSs $A(x)$ to IVIFSs $A(x)$ can be proposed by the following three steps. The sum of membership degree and non-membership degree is considered as a whole calculated by 1-$\pi_A(x)$, then membership degree and non-membership are obtained by dividing 1-$\pi_A(x)$ in portion.

Firstly, calculate the intuitionistic interval.

$$\pi_A(x) = \left[\frac{1}{S}(S - C_S(x)), \frac{1}{S}(S+1-C_S(x))\right], \tag{1}$$

Secondly, determine the criteria is positive/negative. An alternative is considered good when in high compliance with a positive criterion. Oppositely, it is considered unpleasing when in high compliance with a negative criterion.

Thirdly, calculate the membership interval and non-membership interval by assigning 1-$\pi_A(x)$ according to the performance rating $P_N(x)$.

For positive criteria:

$$\mu_{A^+}(x) = \frac{P_N(x)}{N}[1-\pi_A(x)] = \left[\frac{P_N(x)}{N}(1-\pi_{AU}(x)), \frac{P_N(x)}{N}(1-\pi_{AL}(x))\right] \tag{2}$$

$$\nu_{A^+}(x) = \frac{N-P_N(x)}{N}[1-\pi_A(x)] = \left[\frac{N-P_N(x)}{N}(1-\pi_{AU}(x)), \frac{N-P_N(x)}{N}(1-\pi_{AL}(x))\right] \tag{3}$$

For negative criteria, the functions of membership interval and non-membership interval are exchanged:

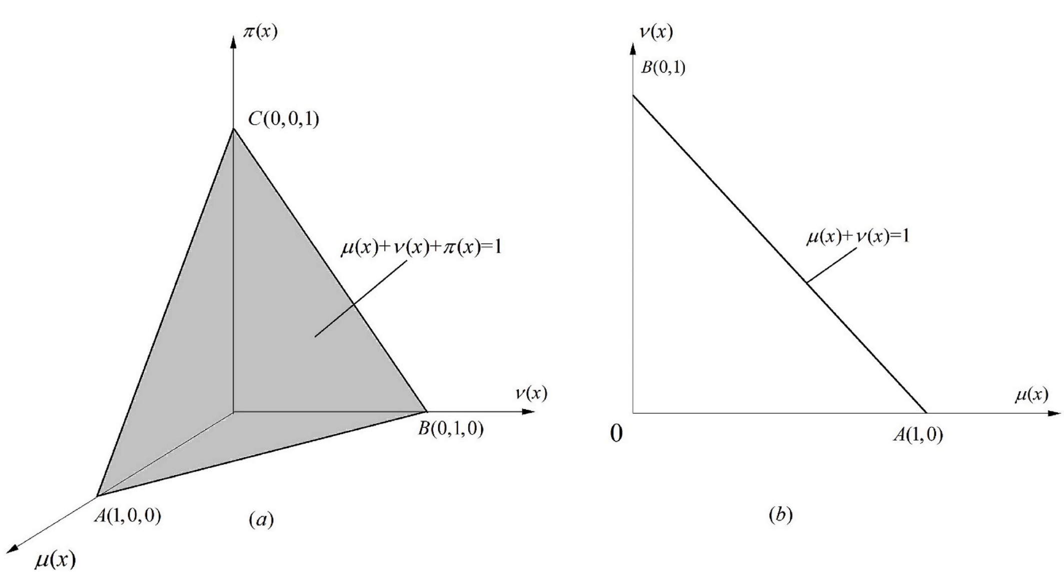

Fig. 1. The difference of intuitionistic fuzzy sets and fuzzy sets.(a) Relationship of membership function, non-membership function, and intuitionistic index of intuitionistic fuzzy sets; (b) Relationship of membership function, non-membership function of fuzzy sets.

$$\mu_{A^-}(x) = \frac{N - P_N(x)}{N}[1 - \pi_A(x)] = \left[\frac{N - P_N(x)}{N}(1 - \pi_{AU}(x)), \frac{N - P_N(x)}{N}(1 - \pi_{AL}(x))\right] \tag{4}$$

$$\nu_{A^-}(x) = \frac{P_N(x)}{N}[1 - \pi_A(x)] = \left[\frac{P_N(x)}{N}(1 - \pi_{AU}(x)), \frac{P_N(x)}{N}(1 - \pi_{AL}(x))\right] \tag{5}$$

$\mu_{A+}(x)$, $\nu_{A+}(x)$ are membership interval and non-membership interval for positive criteria A^+; $\mu_{A\text{-}}(x)$, $\nu_{A\text{-}}(x)$ are membership interval and non-membership interval for negative criteria A^-. The conversion of some DR numbers into IVIF numbers can be seen in Fig. 2.

2.1.3. Entropy and correlation measures of IVIFSs

Existing research of IFSs and IVIFSs mainly includes the scoring functions [65], arithmetic rules [63], aggregation operators [66,67], similarity measures [68], distance measures [42], correlation measures [41,69,70], entropy measures [40], etc. The proposed method is based on entropy and correlation measures of IVIFSs.

Entropy was originally a thermodynamic term, Shannon [71] introduced information entropies to measure the amount of information in decision processes. It can be used to determine the weights of different groups or criteria. According to information entropy theory, the smaller the entropy value is , the more information the group/criterion provides. Then it should be assign a greater weight.

For an exact decision making matrix $Z=(z_{ij})_{m\times n}$, the entropy of C_j can be defined as

$$H_{j=} - k\sum_{i=1}^{m} f_{ij} Inf_{ij} \tag{6}$$

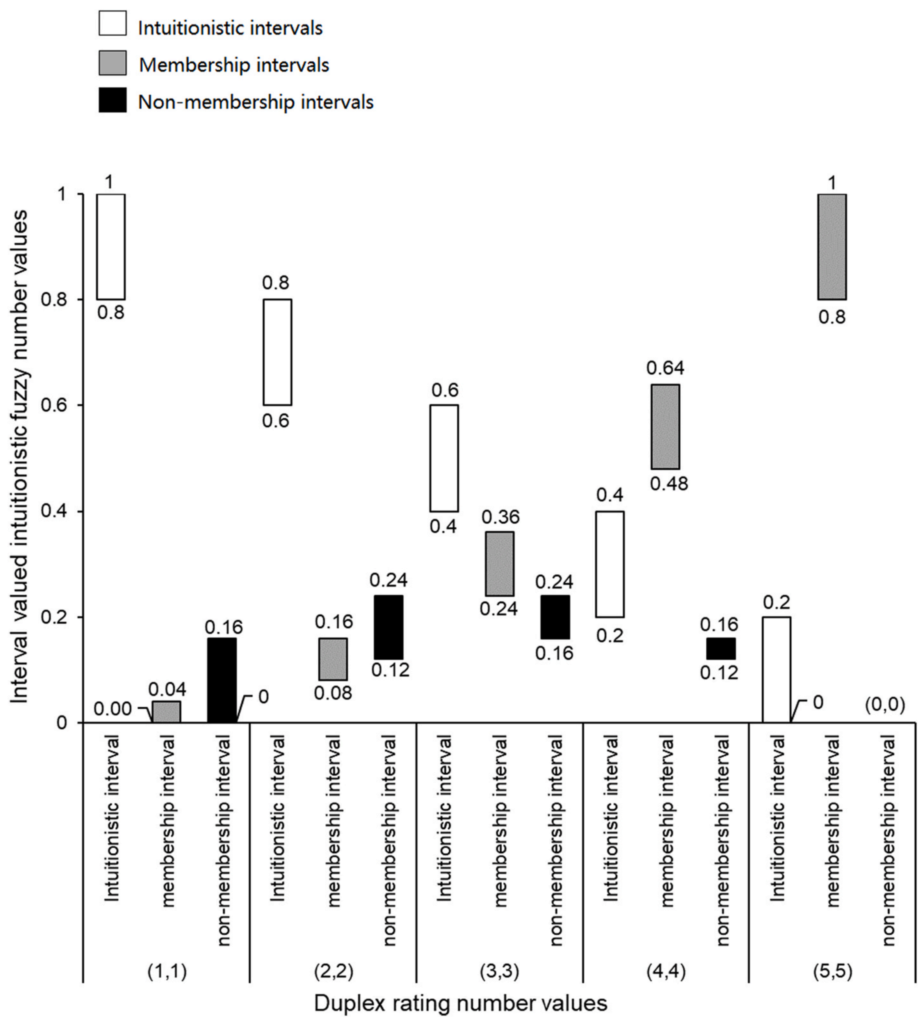

Fig. 2. The mapping from duplex rating numbers to interval-valued intuitionistic fuzzy numbers. Notes: (1) Only taking the conversion of duplex rating numbers (1,1)*, (2,2), (3,3), (4,4), (5,5) as examples; (2) (1,1)* is a duplex rating number ($P_N(x)$,$C_s(x)$), where the performance rating $P_N(x) = 1$, the confidence rating $C_s(x) = 1$; (3) in this case $S = N = 5$, where S denotes the total of confidence ratings, N denotes the total of performance ratings; (4) the criterion is set as positive criterion.

where $f_{ij} = \frac{z_{ij}}{\sum_{i=1}^{n} z_{ij}}, k = \frac{1}{\ln m}$; H_j is called the information entropy of criteria C_j; z_{ij} is the value of alternative A_i under criteria C_j; where $i = 1, \ldots, m$; $j = 1, \ldots, n$.

Kosko [72] put forward fuzzy entropy on the basis of entropy to deal with the uncertainty in information field. Burillo and Bustince [73] proposed intuitionistic fuzzy entropy as the extension of fuzzy entropy. After that, different measures of intuitionistic fuzzy entropies have been introduced by Szmidt and Kacprzyk [43], Parkash et al. [74], and Ye [40]. Then an entropy-based method was brought forward, containing weight determination and ranking method of alternatives by Ye [39]. Ye [41] introduced an effective entropy measure into IVIFSs environment as:

$$I(A) = \frac{1}{n} \sum_{i=1}^{n} \left\{ \sin \frac{\pi \times [1 + \mu_{AL}(x_i) + pW_{\mu A}(x_i) - \nu_{AL}(x_i) - qW_{\nu A}(x_i)]}{4} \sin \frac{\pi \times [1 - \mu_{AL}(x_i) - pW_{\mu A}(x_i) + \nu_{AL}(x_i) + qW_{\nu A}(x_i)]}{4} - 1 \right\} \times \frac{1}{\sqrt{2} - 1}, \tag{7}$$

where *IVIFSs A* is in the universe of discourse *X*.

$W_{\mu A}(x_i) = \mu_{AU}(x_i) - \mu_{AL}(x_i)$, $W_{\nu A}(x_i) = \nu_{AU}(x_i) - \nu_{AL}(x_i)$, p and q are parameters to adjust the proportion of $W_{\mu A}(x_i)$ and $W_{\nu A}(x_i)$, usually $p = q = 0.5$. Ye [75] then proposed the entropy-weighted model of both experts and attributes, which will be used in the proposed MCGDM framework.

Correlation coefficient is a coefficient which can measure the correlation degree of two elements. Dumitrescu introduced this concept into fuzzy sets, and defined the information energy of FSs A as follows: [76,77],

$$K_{Fs}(A, B) = \frac{C_{Fs}(A, B)}{\sqrt{E_{Fs}(A) E_{Fs}(B)}}, \tag{8}$$

where.$E_{Fs}(A) = \sum_{i=1}^{n} {\mu_A}^2(x_i)$, $E_{Fs}(B) = \sum_{i=1}^{n} {\mu_B}^2(x_i)$, $C_{Fs}(A, B) = \sum_{i=1}^{n} \mu_A(x_i)\mu_B(x_i)$,

$E_{FS}(A)$, $E_{FS}(B)$ denotes the information energy of fuzzy set A and B, respectively; $K(A, B)$ denotes the correlation of A and B.

Gerstenkorn and Manko [78] proposed a correlation coefficient of intuitionistic fuzzy set. After that, Burillo and Bustince [79] extended this coefficient to IVIFSs as follows:

$$K_{IVIFs}(A, B) = \frac{C_{IVIFs}(A, B)}{\sqrt{E_{IVIFs}(A) E_{IVIFs}(B)}}, \tag{9}$$

where$C(A, B)_{IVIFs} = \frac{1}{2}[\sum_{i=1}^{n}(\mu_{AL}(x_i)\mu_{BL}(x_i) + \mu_{AU}(x_i)\mu_{BU}(x_i) + \nu_{AL}(x_i)\nu_{BL}(x_i) + \nu_{AU}(x_i)\nu_{BU}(x_i))]$,

$$E_{IVIFs}(A) = \sum_{i=1}^{n} \frac{\mu_{AL}^2(x_i) + \mu_{AU}^2(x_i) + \nu_{AL}^2(x_i) + \nu_{AU}^2(x_i)}{2},$$

$$E_{IVIFs}(B) = \sum_{i=1}^{n} \frac{\mu_{BL}^2(x_i) + \mu_{BU}^2(x_i) + \nu_{BL}^2(x_i) + \nu_{BU}^2(x_i)}{2},$$

where $C(A,B)_{IVIFS}$ denotes the correlation of two IVIFSs A and B; $E_{IVIFs}(A)$, $E_{IVIFs}(B)$ denote the informational intuitionistic energies of two IVIFSs A and B, respectively.

Ye [39] introduced an positive ideal solution $A^* = (1, 0)_{(1 \times m)}$ and a weighted method into calculation, and proposed a new correlation coefficient. The correlation coefficient between alternative and the ideal solution can serve as the final score of the alternative in multi-criteria decision-making problems under intuitionistic fuzzy environment. It is mentioned that the positive ideal solution A* does not exist, it is a solution that is perfect in all aspects. This method can be seen as an extension of TOPSIS, but no negative ideal solution is used in this method, and the similarity measure is replaced by correlation coefficient. This method was then extended to deal with MCDGM problems under IVIFSs environment [41].

2.2. Development of an IVIF entropy-weighted TOPSIS model

With respect to a common MCGDM problem, in which the criterion values are set in different forms by decision makers or experts, and the weight information on criteria and that on decision makers are both unknown, the process of addressing the MCGDM problem mainly includes the following steps [80–83]: Establish and normalize individual decision matrices; Determine the weights of criteria and experts; Merge individual matrices into a group decision matrix by using an reasonable aggregation operator; Use a suitable decision-making method to rank alternatives. For a MCGDM problem, suppose there are n alternatives $(A_1, A_2, \ldots, A_n)$, m criteria for evaluating alternatives $(C_1, C_2, \ldots, C_m)$, and t experts' opinions $(E_1, E_2, \ldots, E_t)$ being considered. This MCGDM problem can be solved by the following entropy-weighted TOPSIS framework with IVIFSs information.

The proposed method can also be divided by following steps:

Step 1: Establish an IVIF individual decision matrix $R = (r_{ij}^k)_{m \times n \times t}$ under three dimensions.

The experts opinions toward each alternative were obtained through questionnaire survey. Experts were asked to give performance ratings $P_{N(i)}^k(C_j)$ of the alternatives according to each criterion. The criteria are divided into positive criteria and negative criteria. In order to collect the confidence degrees of the experts in evaluation processess, each evaluation question is attached to a confidence level question "How much confidence do you have for your assessment?". Similarly, the expert's confidence level of the evaluation is also represented by ratings $(C_{S(i)}^k(C_j))$. The performance rating and confidence rating collected by the questionnaires can be expressed by the proposed DRSs as $((P_{N(i)}^k(C_j), C_{S(i)}^k(C_j)))$ and converted into IVIFSs as $r_{ij}^k = ([\mu_{AL(i)}^k(C_j), \mu_{AU(i)}^k(C_j)], [\nu_{AL(i)}^k(C_j), \nu_{AU(i)}^k(C_j)])$ by Eqs.(1)–(5). The evaluation data can be viewed as a preference matrix $R = (r_{ij}^k)_{m \times n \times k}$ under three dimension of experts, alternatives and criteria. Each element r_{ij}^k in this matrix can show evaluation information of expert E_k on a certain alternative A_i under a certain criteria C_j.

For convenience, it can be written as $r_{ij}^k = ([a_{ij}^k, b_{ij}^k], [c_{ij}^k, d_{ij}^k])$, where a_{ij}, b_{ij}, c_{ij} and d_{ij} denote the lower and upper bounds of membership degree and non-membership degree of evaluation information of each alternative, separately. When expert E_k is determined, an IVIFSs individual preference matrix $R^k = (r_{ij}^k)_{m \times n} = ([a_{ij}, b_{ij}], [c_{ij}, d_{ij}])_{m \times n}$ can be obtained.

$$I_{ij}^{k}=\left\{\sin\frac{\pi\times\left[1+a_{ij}^{k}+p\left(b_{ij}^{k}-a_{ij}^{k}\right)-c_{ij}^{k}-q\left(d_{ij}^{k}-c_{ij}^{k}\right)\right]}{4}+\sin\frac{\pi\times\left[1-a_{ij}^{k}-p\left(b_{ij}^{k}-a_{ij}^{k}\right)+c_{ij}^{k}+q\left(d_{ij}^{k}-c_{ij}^{k}\right)\right]}{4}-1\right\}\times\frac{1}{\sqrt{2}-1} \tag{10}$$

Step 2: Determine the experts' weights using entropy-weighted model. Expert weight z_{ij}^{k} is defined as the allocated weight of expert E_k evaluating alternative A_i under criterion C_j. z_{ij}^{k} can be considered as a member of group expert weight matrix $Z=(z_{ij}^{k})_{m\times n\times t}$, also a member of weight matrix for expert k $Z^k=(z_{ij}^{k})_{m\times n}$. As mentioned above, the preference matrix is three-dimensional, elements in this matrix own its entropies. The IVIFSs information entropies of elements are calculated by Eq. (10) [41]. According to the information entropy theory, each element r_{ij}^{k} has an entropy value I_{ij}^{k} that can quantify the amount of information it contains. Also, the entropy value I_{ij}^{k} can be a member of an individual entropy matrix $I=(I_{ij}^{k})_{m\times n\times t}$. Hence, the lower the IVIF entropy value is, the higher the weight this expert should be assigned to by Eq. (11).

where $0\le I_{ij}^{k}\le 1, i=1,\dots,n; j=1,\dots,m; k=1,\dots,t$; and $p,q\in[0,1]$ are two fixed numbers.

$$z_{ij}^{k}=\frac{1-I_{ij}^{k}}{t-\sum_{k=1}^{t}I_{ij}^{k}}, \tag{11}$$

where $0\le I_{ij}^{k}\le 1$, $z_{ij}^{k}\in[0,1]$, $i=1,\dots,n; j=1,\dots,m; k=1,\dots,t; p, q\in[0,1]$ are two fixed numbers; and p and q are parameters used to adjust the proportion of $W_{\mu A}(x_i)$ and $W_{\nu A}(x_i)$,usually $p=q=0.5$.

Step 3: Formulate a group IVIFSs preference matrix R' by integrating the opinions of all experts. The following weighted equation helped to degrade the three dimensional matrix $R=(r_{ij}^{k})_{m\times n\times k}$ into two-dimensional group preference matrix $R^{'}=(r_{ij}^{'})_{m\times n}$.

$$r_{ij}^{'}=\sum_{k=1}^{t}z_{ij}^{k}r_{ij}^{k}, \tag{12}$$

where $i=1,\dots,n; j=1,\dots,m; k=1,\dots,t.$

Step 4: Determine the weights of criteria by entropy-weighted model.

Similarly, entropy values of criteria and the entropy-based weights of criteria can be calculated as Eq. 13 and 14 [41]:

$$z_j=\frac{1-I_j}{n-\sum_{j=1}^{n}I_j}, \tag{13}$$

$$I_j=\frac{1}{m}\sum_{i=1}^{m}\left\{\begin{array}{l}\sin\dfrac{\pi\times\left[1+a_{ij}+p\left(b_{ij}-a_{ij}\right)-c_{ij}-q\left(d_{ij}-c_{ij}\right)\right]}{4}+\\ \sin\dfrac{\pi\times\left[1-a_{ij}-p\left(b_{ij}-a_{ij}\right)+c_{ij}+q\left(d_{ij}-c_{ij}\right)\right]}{4}-1\end{array}\right\}\times\frac{1}{\sqrt{2}-1} \tag{14}$$

where $u_j\in[0,1]$; $\sum_{j=1}^{n}Z_j=1; j=1,\dots,m$; I_j is the entropy value of C_j; Z_j is the entropy-based weight of C_j.

Step 5: Using an extended TOPSIS method to rank all the alternatives.

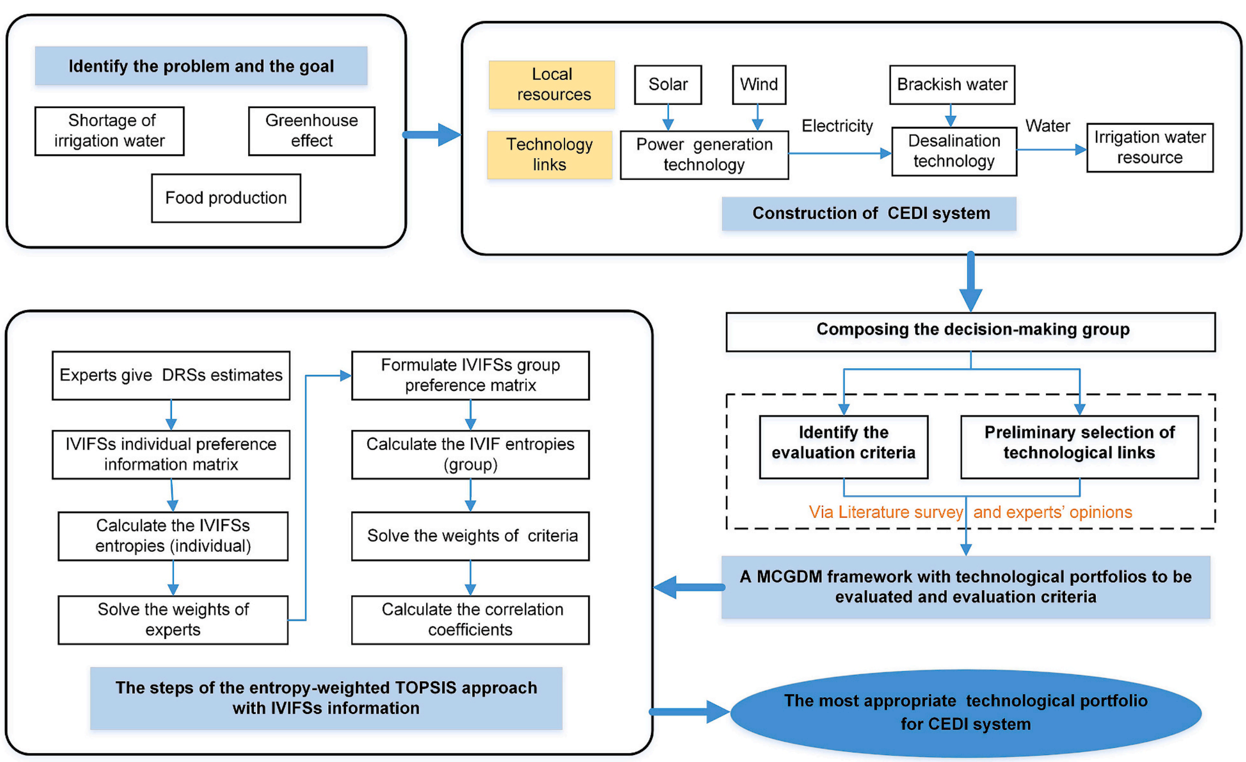

Fig. 3. The flowchart of case study.

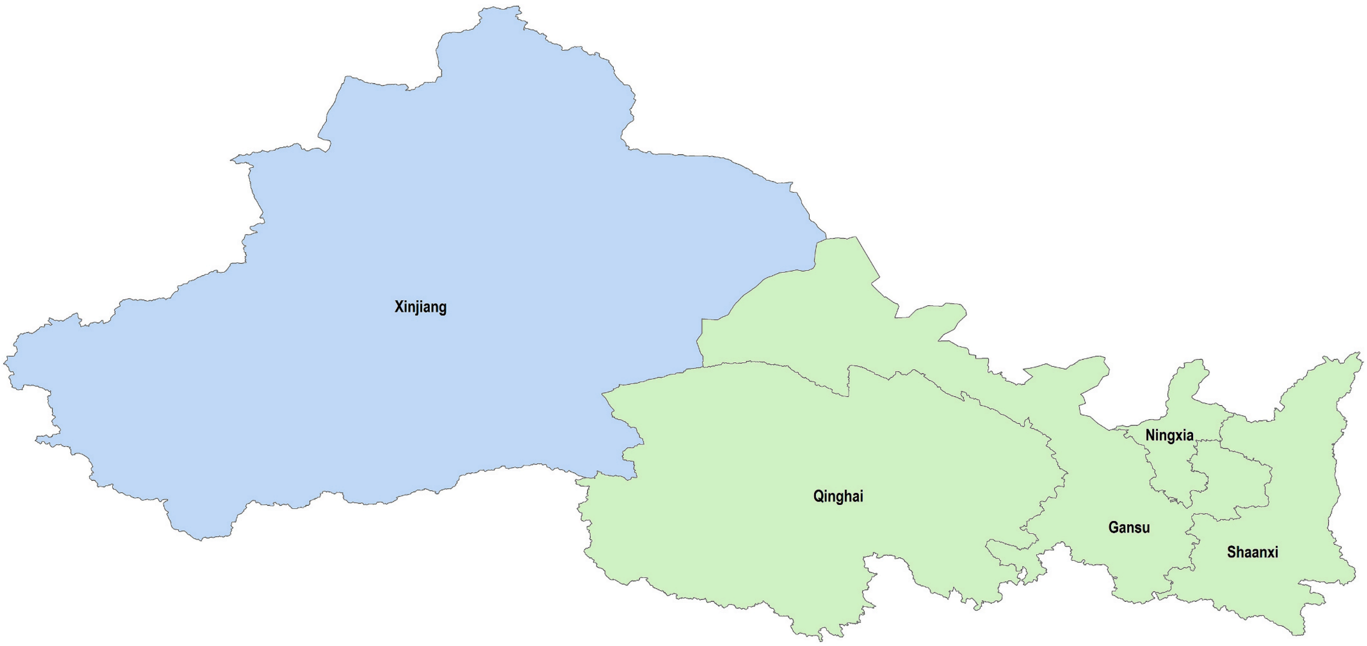

Fig. 4. The map of northwest provinces of China showing the study area.

The ideal solution concept has been widely used in MCDM approach, especially studies related to VIKOR and TOPSIS. VIKOR aims to realize a compromise solution by maximize the group effect and minimize the individual regrets. The proposed method can be seen as an extension of TOPSIS, which can depict the similarity between the positive solution and the alternative by correlation coefficient, but no negative ideal solution is used in this method. Although the ideal solution does not exist in real world, it does provide an useful theoretical construct to evaluate alternatives. The ideal positive solution of the proposed method under IVIFSs environment can be defined as:

$A^* = \{\langle C_j, \alpha_j^*(C_j)\rangle | C_j \in C\} = \{\langle C_j, [1,1], [0.0]\rangle\}$ for "excellence". Then the correlation coefficient between an alternative A_i and the ideal solution A^* can be measured by the weighted correlation coefficient W_{IVIFSi} [75]:

$$W_{IVIFSi}(A^*, A) = \frac{\sum_{j=1}^{n} \frac{z_j\left(a_{ij}+b_{ij}\right)}{2}}{\sqrt{\sum_{j=1}^{n} \frac{z_j\left(a_{ij}^2+b_{ij}^2+c_{ij}^2+d_{ij}^2\right)}{2}}} \tag{15}$$

The larger the value of weighted correlation coefficient W_{IVIFSi} is, the closer alternative A_i is to the ideal alternative A^*. Finally, all the alternatives can be ranked according to the values of the weighted correlation coefficients.

3. Application

The flowchart of this case study can be seen in Fig. 3.

3.1. Study area

To demonstrate the practicability of this model, it was applied to Xinjiang Uygur Autonomous Region in the northwestern China (Fig. 4). Xinjiang Uygur Autonomous Region is the largest Chinese administrative division and has an area over 1.6 million km^2, which is approximately one sixth of China's territory. Due to its long distance from the ocean, a typical temperate continental arid climate is formed in this region, and the annual average precipitation is only 163.3 mm. Owing to low precipitation, Xinjiang is a high irrigation-dependent region. Although Xinjiang is lacking freshwater, the water resources is only 3,130 m^3 per capita, the brackish water potential of Xinjiang is noticeable. The brackish water can be extracted is 1.742 billion m^3 per year, while the actual mining rate is only 15.2%.

Xinjiang is a region with abundant wind and solar energy resources. The wind energy reserves of Xinjiang reach 957 million kilowatts. The wind power installed capacity of Xinjiang gradually increased to 19,912 MW by 2018 [84]. The total solar radiation in Xinjiang varied from 5, 440 to 6,280 MJ·m^{-2}, The annual average sunshine hours in Xinjiang is 2,808.6 h, which proves that PV is applicable in Xinjiang. But the total energy production of wind and solar accounts for less than 9.3% of the total, which implicated further development of solar and wind power generation are still needed. The great potential of wind and solar, and the widely distributed brackish water make it possible to desalinate brackish water for irrigation and promote food production in this region.

3.2. Identification of evaluation criteria

In order to evaluate CEDI systems with different performances in various aspects, and obtain the most suitable technology portfolio in arid regions, multiple criteria need to be considered. Six criteria related to economy, agriculture, environment and system performance were determined by consulting experts, which are pre-investment (PI), operating costs (OC), product yield (PY), system stability (SS), system adaptability (SA), and integrated environmental impact (EI). The classification and scope of each criterion can be seen in Table 1.

In this study, system stability, product yield and system adaptability were defined as positive criteria. Agricultural benefits are expected to increase. Also, it is expected the system can maintain stable operation in a long time. Similarly, higher scores of the system adaptability mean the greater range that the system can be applied to and the better performance under external disturbances. While the rest of criteria are considered negative criteria, because it is hoped that the selected alternative is more economical and environmentally friendly.

3.3. Preliminary screening of technologies and formulation of technology portfolios

The study area is located in the arid region of Northwest China, the lack of irrigation water hinders food production in this region, but the

Table 1
The classification, description, and what may be included in the selected criteria.

Dimensions	Criteria	P/N	Description	What this criteria may include
Economical	PI	N	Investment before the operation of CEDI systems	Pre-treatment process costs; the equipment investment of power generation, desalination, and irrigation; the investment of greenhouse.
	OC	N	Expenses incurred during the operation of CEDI systems	Labor costs; consumable materials costs; costs of equipment parts replacement; maintenance costs; costs of disposal of wastewater and waste equipment parts.
Agricultural	PY	P	Agricultural product yield	The product of crops irrigated by CEDI systems.
Environmental	EI	N	Integrated environmental impact of CEDI systems	Noise pollution; pollution of influent pretreatment; concentrated brine disposal; waste parts disposal.
System performance	SS	P	Stability of CEDI systems	The stability of water quality and quantity; the stability of the energy supply; the maintenance degree of the system's working capacity as the working years grows.
	SA	P	Adaptability of CEDI systems	The adaptation to product water requirements of different quality and quantity; the adaptation to water influents of different quality and quantity; the adaptation to different climatic conditions and hydrological situation.

Notes: P, N, PI, OC, PY, EI, SS, and SA are abbreviations for positive criteria, negative criteria, pre-investment, operating cost, product yield, environmental impact, system stability, and system adaptability.

abundant solar, wind, and brackish water resources bring a chance of promoting food production. The CEDI system contains irrigation water quality technology link, power generation technology link, desalination technology link. Different options in each technology link will have impact on the final performance of the systems in terms of economy, environment and society. To make the workloads manageable, a preliminary screening of technology link alternatives with greater potential was conducted. The preliminary screening process is conducted based on the characteristic of the study area, where solar, wind, and brackish water resources are abundant.

3.3.1. Power generation technologies

Arid regions in northwest China have limited freshwater but abundant energy available in renewable energy sources, such as wind, solar. For the higher applicability of this CEDI system in the study area, only mainstream power generation technologies using wind and/or solar were being considered. Photovoltaic power generation (PV) and hybrid photovoltaic-wind power generation (PV-wind) were considered as alternatives of power generation technology link.

To find supplemental energies for conventional fuels with multiple harmful effects, researchers have explored various renewable energies such as solar, wind, fuel cell stack, biomass, tidal energy and so on. Solar and wind have been widely used for their harmless impact and effective cost [86–88]. Technologies that use solar energy including PV, photochemical power generation, optical induction power generation, and photo-bioelectric power generation but only PV has become a popular technology. Substantial studies aims to overcome the association of PV and wind [87–90]. PV-wind system are more stable and efficient than simple PV or wind because PV and wind are complementary in power generation [91].

3.3.2. Desalination technologies

Desalination technology has a significant impact on the quality of product water and system efficiency of the system. Reverse osmosis (RO) and Capacitive deionization (CDI) were selected as the alternatives of desalination technology link through literature review and experts survey. Membrane separation processes have been utilized extensively due to their lower energy consumption compared to thermal methods [92]. Among all the membrane methods, RO gained much attention for its significant economic advantages for lower production and maintenance costs than thermal processes [93]. RO uses pressure difference between two sides of membrane as driving force to separate solvent from solution. Numerous membranes with various separation characteristics have been available for multiple use [94]. Furthermore, simplicity and modularity, rational installation space, and lower environmental impact make RO friendly to use. For the desalination of brackish water, RO is the most common method.

CDI is an electrochemical method, which remove salt from aqueous solutions by taking advantage of the excess ions adsorbed in the electrical double layer region at an electrode-solution interface when the electrode is electrically charged by an external power supply. CDI was first introduced by Caudle et al., in 1960s [95], who used porous carbon electrodes in a flow-through mode for water desalination. CDI was reported as [96] an alternative to membrane desalination technologies like RO and electrodialysis, which have the potential to be energy efficient to dilute brackish water in 0.594 kWh/m^3 on the industrial type bench scale unit [97]. CDI has not yet developed to become a mature commercial technology, but for low molar concentration streams like brackish water, CDI is a promising alternative to established technologies such as RO [98]. Also, CDI powered by PV is considered as agronomic applicable in a farm scale [99].

3.3.3. Desalinated water salinity for irrigation

Water salinity is crucial for agricultural crop production and the associated economic return. According to the degree of mineralization, the water source is divided into saltwater, brackish water and freshwater resources in this study. Two different settings of irrigation water sources were discussed, one was alternately irrigated with brackish-fresh water, refers to utilizing freshwater irrigation before and during seedling, and brackish water irrigation in other periods. And the other was only irrigated with freshwater.

Brackish water are being gradually diverted to irrigation sector. But

Table 2
The composition of technology portfolios.

	Technology Link	PCA	PCF	PRF	HCA	HCF	HRF
Power generation	Photovoltaic	✓	✓	✓			
	Hybrid wind-photovoltaic				✓	✓	✓
Desalination	Capacitive deionization	✓	✓		✓	✓	
	Reverse osmosis			✓			✓
Desalinated water quality for irrigation	Alternating brackish-fresh water	✓			✓		
	Freshwater		✓	✓		✓	✓

Table 3
Expert 1's DRSs individual preference matrix.

Portfolios	Pre-investment	Operating Cost	Product yield	Environmental impact	System stability	System adaptability
PCA	(4,4)*	(3,4)	(3,3)	(4,3)	(3,3)	(3,3)
PCF	(4,4)	(3,4)	(4,3)	(3,3)	(3,3)	(3,3)
PRF	(4,4)	(4,3)	(4,3)	(3,3)	(4,3)	(4,3)
HCA	(5,4)	(3,4)	(3,3)	(4,3)	(4,3)	(3,3)
HCF	(5,4)	(3,3)	(4,3)	(3,3)	(4,3)	(3,3)
HRF	(5,4)	(4,3)	(4,3)	(3,3)	(4,3)	(4,3)

Notes: (1) (4,4) * is a duplex number ($P_N(x)$,$C_s(x)$), where the performance rating $P_N(x) = 4$; the confidence rating $C_s(x) = 4$; (2) in this case $S = N = 5$; where S denotes the total of confidence ratings; N denotes the total of performance ratings.

Table 4
Converted Expert 1's IVIFSs individual preference matrix.

Portfolios	Pre -investment	Operating Cost	Product yield	Environmental impact	System stability	System adaptability
PCA	([0.12,0.16], [0.48,0.64])	([0.24,0.32], [0.36,0.48])	([0.24,0.36], [0.16,0.24])	([0.08,0.12], [0.32,0.48])	([0.24,0.36], [0.16,0.24])	([0.24,0.36], [0.16,0.24])
PCF	([0.12,0.16], [0.48,0.64])	([0.24,0.32], [0.36,0.48])	([0.32,0.48], [0.08,0.12])	([0.16,0.24], [0.24,0.36])	([0.24,0.36], [0.16,0.24])	([0.24,0.36], [0.16,0.24])
PRF	([0.12,0.16], [0.48,0.64])	([0.08,0.12], [0.32,0.48])	([0.32,0.48], [0.08,0.12])	([0.16,0.24], [0.24,0.36])	([0.24,0.36], [0.16,0.24])	([0.32,0.48], [0.08,0.12])
HCA	([0,0],[0.60,0.80])	([0.24,0.32], [0.36,0.48])	([0.24,0.36], [0.16,0.24])	([0.08,0.12], [0.32,0.48])	([0.32,0.48], [0.08,0.12])	([0.24,0.36], [0.16,0.24])
HCF	([0,0],[0.60,0.80])	([0.16,0.24], [0.24,0.36])	([0.32,0.48], [0.08,0.12])	([0.16,0.24], [0.24,0.36])	([0.32,0.48], [0.08,0.12])	([0.24,0.36], [0.16,0.24])
HRF	([0,0],[0.60,0.80])	([0.08,0.12], [0.32,0.48])	([0.32,0.48], [0.08,0.12])	([0.16,0.24], [0.24,0.36])	([0.32,0.48], [0.08,0.12])	([0.32,0.48], [0.08,0.12])

Notes: ([0.12,0.16],[0.48,0.64]) * is an interval-valued intuitionistic fuzzy number (IVIFN) expressed as ([$\mu_{AL}(x)$, $\mu_{AU}(x)$],[υ_{AL} (x),$\upsilon_{AU}(x)$]), where $\mu_{AL}(x)$=0.12, $\mu_{AU}(x)$=0.16, $\upsilon_{AL}(x)$=0.48, and $\upsilon_{AU}(x)$=0.64; $\mu_{AL}(x)$, $\mu_{AU}(x)$ denote the lower and upper bounds of membership interval; $\upsilon_{AL}(x)$,$\upsilon_{AU}(x)$ denote the lower and upper bounds of non-membership interval.

irrigation water quality degradation from salinity may pose food production and soil at risk at long term [19]. Blending brackish water and fresh water to keep the resultant salinity below threshold, or their cyclic application by scheduling irrigation with salty water at less salt sensitive stages are important attempts to promote food production in arid regions [100]. However, Shalhevet mentioned blending of saline with non-saline water is a questionable practice compared to alternating brackish-fresh water irrigation [101].

3.3.4. To-be-assessed CEDI alternatives

This system cultivates salt-tolerant economic crops in greenhouse, applying drip irrigation under the membrane. It should be noted that the product water of CDI can be set as brackish water or freshwater standards. RO only products freshwater. In addition, if the water source in the dry area meets the brackish water standard, it can also be used directly in alternating brackish-fresh water irrigation. By removing some unreasonable technology portfolios like portfolios combining RO and alternating brackish-fresh water irrigation, six technology portfolios to be evaluated were determined as shown in Table 2.

3.4. Data collection and treatment

Questionnaires with seven questions were used to collect expert opinions, and eleven valid questionnaires were collected. The first six questions were set as the matrix scale questions related to the criteria. Each matrix scale question includes 12 secondary questions, six of which were used to collect the performance ratings of each alternative under a certain criterion. The other six were used to judge the confidence ratings of the experts when they are evaluating portfolios, how much confidence do they have in their judgements. The options for the matrix scale were five ratings of magnitude from 1 to 5. The seventh question was set to collect the research background of experts. Ratings of performance and confidence levels can be collected as DRSs as the following Table 3, and then they were transformed into 11 individual matrices, and the IVIFSs individual preference matrix of expert 1 is shown as an example (Table 4).

4. Results and discussions

4.1. Expert weights

According to the proposed method, expert weights can be expressed as a three-dimensional matrix. They are determined by the entropy of each element in the IVIFSs individual preference matrix, which varied in experts, criteria, and portfolios. The distribution of expert weights of the case study is shown in Fig. 5. It can be seen that the same expert was assigned different weights evaluating different portfolios under same criterion or evaluating the same portfolio under different criteria. This shows that when the importance differences of experts in the assessments of different portfolios and different criteria were not taken into account, a large amount of information would be lost and the final decision would be influenced. Taking Expert 1(E_1) evaluating different portfolios under pre-investment as an example, in evaluating PCF and PRF, $E_1$was allocated to relatively lower weights than evaluating other portfolios. This may because the E_1 knows more about hybrid power generation than photovoltaic power generation.

After obtaining the expert weights, then the IVIFSs group preference matrix (Table 5) can be obtained by the aggregation of different expert opinions. It can be seen that the sum of the membership degree and the non-membership degree of each IVIF number is relatively low, which causes the large differences between the positive ideal solution and each portfolio.

4.2. Criteria weights

The weights of pre-investment, operating cost, product yield, environmental impact, system stability, and system adaptability are 0.233, 0.117, 0.283, 0.079, 0.143 , and 0.146, respectively. The criteria were ranked as product yield > pre-investment > system adaptability > system stability > operating cost > environmental impact.

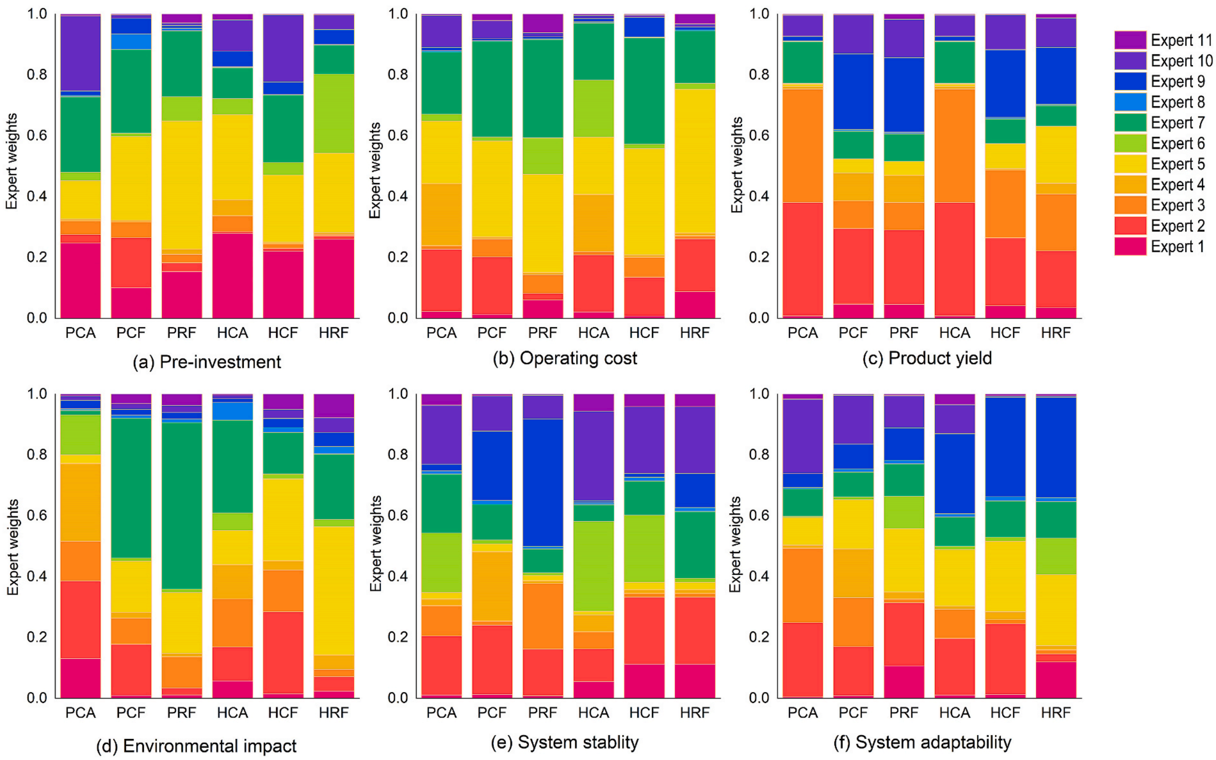

Fig. 5. The distribution of expert weights. (a) experts' weights of evaluating portfolios according to pre-investment; (b) experts' weights of evaluating portfolios according to operating cost; (c) experts' weights of evaluating portfolios according to product yield; (d) experts' weights of evaluating portfolios according to environmental impact; (e) experts' weights of evaluating portfolios according to system stability; (f) experts' weights of evaluating portfolios according to system adaptability. Notes: PCA is a technology portfolio of photovoltaic power generation, capacitive deionization, and alternating brackish-fresh water irrigation; PCF is a technology portfolio of photovoltaic power generation, capacitive deionization, and fresh water irrigation; PRF is a technology portfolio of photovoltaic power generation, reverse osmosis, and freshwater irrigation;HCA is a technology portfolio of hybrid photovoltaic-wind power generation, capacitive deionization, and alternating brackish-fresh water irrigation; HCF is a technology portfolio of photovoltaic-wind power generation, capacitive deionization, and freshwater irrigation; HRF is a technology portfolio of photovoltaic-wind power generation, reverse osmosis, and freshwater irrigation.

Table 5
Aggregated group IVIFSs preference matrix.

Portfolios	Pre-investment	Operating cost	Product yield	Environmental impact	System stability	System adaptability
PCA	([0.12,0.16], [0.43,0.58])	([0.20,0.27], [0.37,0.50])	([0.55,0.74], [0.03,0.04])	([0.24,0.33], [0.27,0.38])	([0.44,0.59], [0.12,0.17])	([0.55,0.74], [0.03,0.04])
PCF	([0.08,0.11], [0.51,0.68])	([0.14,0.18], [0.46,0.62])	([0.51,0.70], [0.04,0.06])	([0.13,0.18], [0.43,0.58])	([0.42,0.58], [0.12,0.16])	([0.44,0.60], [0.12,0.16])
PRF	([0.05,0.07], [0.47,0.65])	([0.04,0.06], [0.51,0.70])	([0.51,0.69], [0.04,0.06])	([0.06,0.08], [0.50,0.67])	([0.48,0.66], [0.04,0.06])	([0.38,0.54], [0.10,0.14])
HCA	([0.04,0.06], [0.50,0.68])	([0.26,0.35], [0.33,0.44])	([0.55,0.74], [0.03,0.04])	([0.12,0.16], [0.42,0.57])	([0.48,0.66], [0.05,0.07])	([0.39,0.56], [0.08,0.11])
HCF	([0.01,0.02], [0.56,0.76])	([0.08,0.11], [0.49,0.66])	([0.54,0.73], [0.02,0.03])	([0.22,0.30], [0.29,0.41])	([0.41,0.57], [0.11,0.16])	([0.41,0.58], [0.08,0.11])
HRF	([0.02,0.03], [0.55,0.74])	([0.12,0.17], [0.44,0.59])	([0.55,0.74], [0.01,0.02])	([0.15,0.21], [0.35,0.49])	([0.41,0.57], [0.11,0.16])	([0.38,0.55], [0.07,0.10])

CDI is considered to be much less expensive to operate than RO that requires membrane replacement in later use. The system stability and system adaptability were used to assess system performance in two different aspects, and the weights given were not much different. In this case, the weight of the environmental impact was lower than the weight of the operating cost. It should be noted that product yield gained the largest weight, and it may be related to the following reasons. First, the products yield is the thing that stakeholders (farmers or decision makers) and experts focus most. Second, in this study, almost all experts have rich agricultural knowledge, more useful information about agriculture can be given than other aspects.

4.3. *Alternative scores*

In this study, the correlation coefficient between the portfolio and the positive ideal solution served as the final score to rank all the portfolios. The higher the correlation between a portfolio and the positive ideal solution is, the closer it is to "excellence". It was used to screen out the most suitable CEDI technology portfolio in Xinjiang. The scores of PCA, PCF, PRF, HCA, HCF, and HRF were 0.748, 0.640, 0.593, 0.673, 0.602, and 0.612. Therefore, it can be determined that the most suitable portfolio is PCA, which is highly recognized by experts. PCA has relatively low pre-investment and high adjustability of water production, which is also convenient to operate and maintain. PCF is considered as low operating cost and pre-investment than other portfolios. HCA got

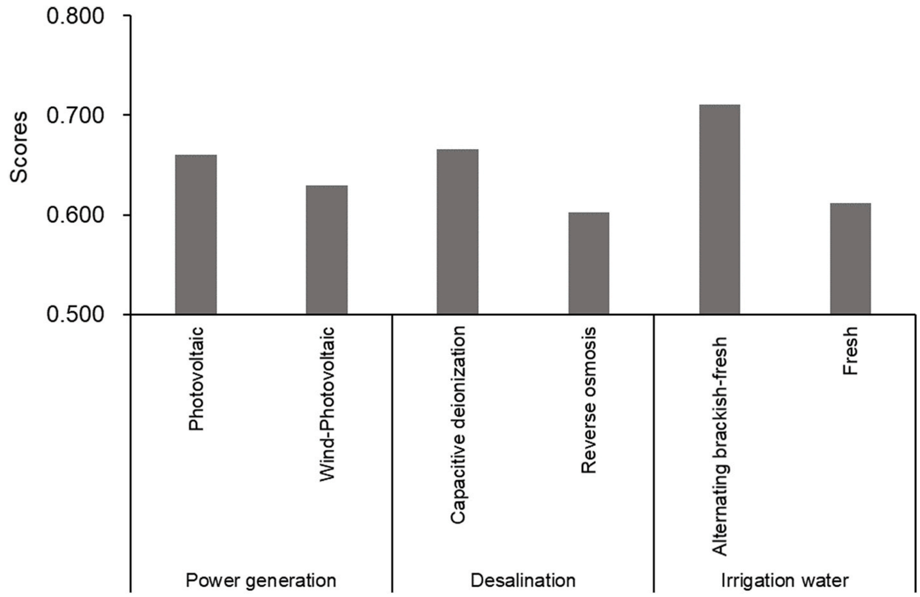

Fig. 6. The average scores of portfolios applying different technologies in different technology links. Notes: The correlation coefficient between the portfolio and the positive ideal solution served as the final score to rank all the portfolios.

Table 6
The settings for sensitivity analysis of expert weight, criteria weight, and hesitant parameter.

Type		Amounts	Settings
Expert weight analysis	Expert E_x in dominance	11	For expert E_x,$Z^x = (z_{ij}^x)_{m\times n}$ =$(0.5)_{m\times n}$; and for the rest of experts $E_k(k\neq x)$, $Z^k = (z_{ij}^k)_{m\times n}$=$(0.05)_{m\times n}$;
	Equal expert weight	1	$(z_{ij}^k)_{m\times n\times t} = \left(\frac{1}{11}\right)_{m\times n\times t}$;
Criteria weight analysis	Criterion C_y in dominance	6	For dominant criterion C_y, $z_y = 0.35$; and for the rest of criteria C_j, $z_j = 0.13(y\neq j)$;
	Equal criterion weight	1	$z_j = 1/6$ for all criteriaC_j;
Hesitant parameter analysis	No confidence rating	1	Assume that the hesitant degree of experts do not exist, and only the performance ratings were used.

Notes: (1) In all settings of parameters, their scores of portfolios were calculated by Eq.(15); (2) In all settings of experts and hesitant parameter, their criteria weights were calculated by Eq.(13, 14); (3) the correlation coefficient between the portfolio and the positive ideal solution served as the final score to rank all the portfolios.

lower scores than PCA, which has good performance in operating cost, product yield, and system stability. HRF and HCF were very alike and got similar scores. HCF didn't get a good score because of its high pre-investment , and the poor system adaptability. PRF got the lowest score is related to its poor performance in operating cost, system adaptability, and environmental impact. The impact of PRF on the environment mainly concludes the noise impact of the hybrid power generation system, the membrane replacement pollution in the RO technology, and the pollution of the concentrated brine disposal process and so on.

Since each portfolio is evaluated as a whole after combining technology links, the contribution of each link to the overall score cannot be separated. Therefore, according to the different technologies in each link, the average scores (Fig. 6) of the portfolios using the same technology were used to discuss the contribution of technologies. The average score of portfolio using PV is higher than that of PV-wind, which reflects PV is considered better than PV-wind. Also, the average score of portfolios using CDI is higher than that of RO, and the average score of portfolios using alternating brackish-fresh water irrigation is higher than that of freshwater irrigation. From this aspect, PCA get the highest score for it combined three technologies considered better. However, the worst portfolio is PRF combining PV, RO, and freshwater irrigation not HRF, which combine PV-wind, RO, and freshwater irrigation. Because the performance of the portfolio is not just about the combination of all the technologies but also the interactions among different links. The combination of PV-wind and RO is considered more rational than that of PV and RO, because the energy provided by wind-PV is more stable to maintain the operation of RO for its higher energy consumption per hour.

4.4. Sensitivity analysis

Sensitivity analysis has been done to validate the robustness of the obtained ranking, 20 settings of different parameters (not including the proposed method) were listed in Table 6.

Expert weight analysis showed it is crucial to objectively assign weights to experts. When different expert is in dominance for all aspects, the criteria weights (Fig. 7) varied a lot according to their preference and the ranking of alternatives (Fig. 8) fluctuated intensely. For instance, when E_1 is in dominance, the alternative ranked as PRF>PCF>PCA>HRF>HCF>HCA; while for E_8, HRF > PCF > PRF > PCA > HCF > HCA, which were quite different. Hence it is not wise for an expert to dominate all aspects in an evaluation progress, because the opinions of other experts, who are not in dominance, may be overlooked in certain degree. In addition, the setting of equal expert weight (EEW) was also considered, where all experts were assigned the same weight, and the criteria weights were also calculated by entropy-weighted method. From Fig. 7, It can be seen that the difference of criteria weights is very extreme in EEW. For example, product yield accounts for more than 30% of the total, but the weights of operating cost, and environmental impact are very low. Evenly or dominant weight assignment to a certain expert on all aspects could have huge impacts on

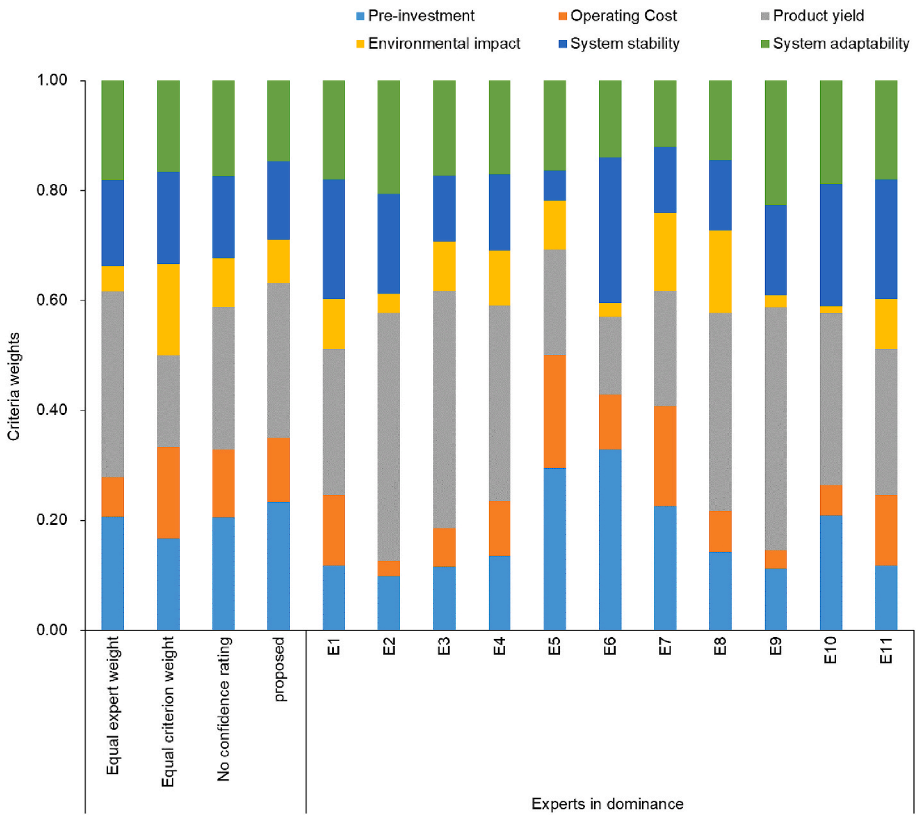

Fig. 7. Criteria weights under different settings. Notes: (1) NCR,EEW, and ECW are abbreviations for no confidence rating, equal expert weight, and equal criterion weight; (2) When expert E_x is in dominance, z_{ijx}=0.5; and for the rest of experts E_k, z_{ijk}=0.05.; (3) NCR does not consider experts' hesitation degree, and the confidence ratings were not used, experts were considered of full confidence of their judgements; (4) In EEW, Expert weight z_{ijk}=1/11; (5) the criteria weights of ECW are z_k=1/6; (6) the correlation coefficient between the portfolio and the positive ideal solution served as the final score to rank all the portfolios.

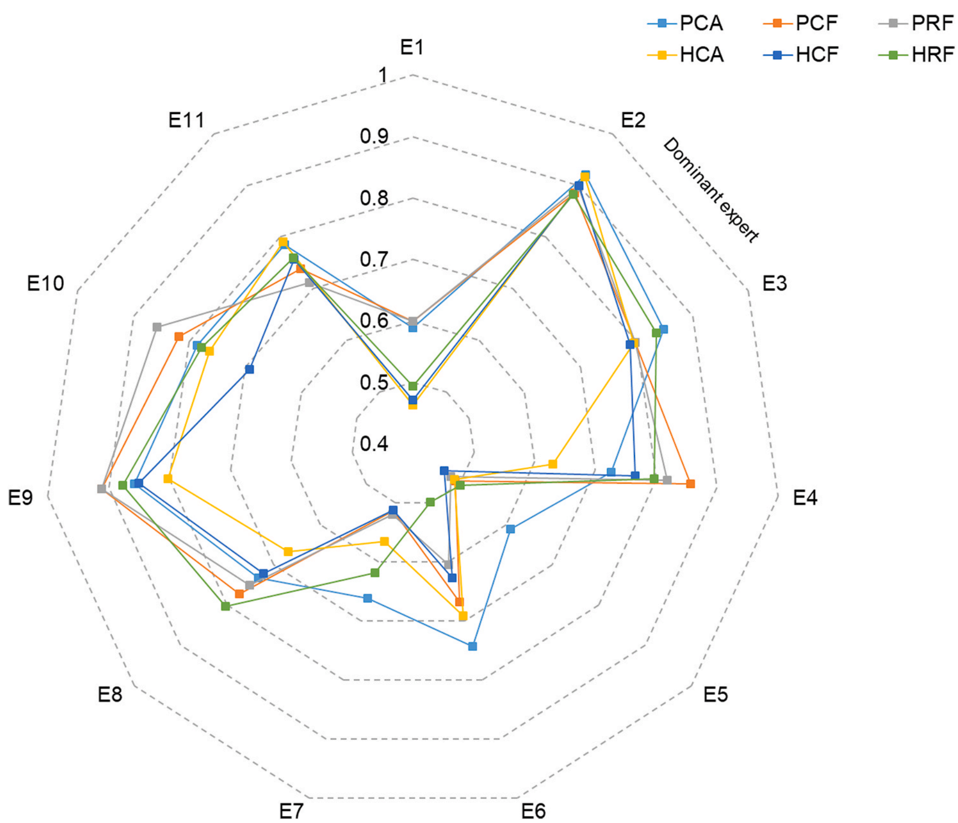

Fig. 8. Portfolio scores under different settings of expert weights. Notes: (1) When expert E_x is in dominance, z_{ijx}=0.5; and for the rest of experts E_k, z_{ijk}=0.05. (2) the correlation coefficient between the portfolio and the positive ideal solution served as the final score to rank all the portfolios.

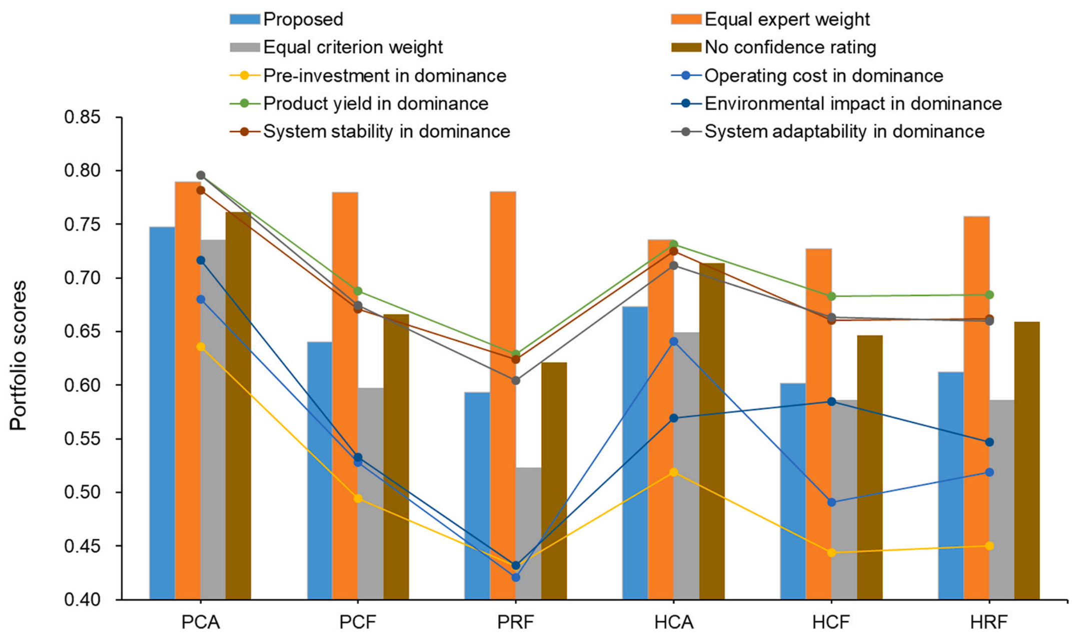

Fig. 9. Portfolio scores under different settings of criteria weights. Notes: (1) when a criterion C_y is in dominance, z_y=0.35; and for the rest of criteria C_j, $z_j = 0.13$; (2) the correlation coefficient between the portfolio and the positive ideal solution served as the final score to rank all the portfolios.

the ranking of portfolios, which illustrated the importance of assigning the weights of expert objectively.

Then criterion weight analysis (Fig. 9) has been done, including settings of criteria in dominance and the equal criterion weight (ECW). The rankings under all settings of criteria weights were relatively stable except when environmental impact is in dominance. This may because criteria were not assigned to weights that are too overwhelm as expert weights.

At last, the comparison of no confidence rating (NCR) and the proposed method was conducted, as shown in Fig. 9, the scores of no confidence rating are higher than that of the proposed method, this may be caused by the hesitant degree that is ignored in this setting. When hesitant degree increases, the portfolio with the same performance rating will become farer from the positive ideal solution. Different settings of parameters lead to varied weights of criteria, although the rankings of the proposed and NCR remained same.

The sensitivity analysis showed the advantage of the screened PCA is significant, which ranked first in 12 of total 20 settings.

4.5. Discussions

CEDI system aims to promote food production by diluting brackish water for irrigation driven by clean energy like wind or solar, which will release far less CO_2, than traditional fuels. To quantify the CO_2 emission of per cubic meter desalinated water powered by traditional fuels and by clean energy (photovoltaic in this case), two equations were proposed as follows:

$$E_{RO} = \frac{3.6 \times 10^{-6}}{\eta} P_{RO} f_{\text{Thermal}}, \quad (16)$$

$$E_{PV-CDI} = P_{CDI} f_{PV}, \quad (17)$$

$E_{RO,}$ the unit CO_2 emission of reverse osmosis driven by thermal power, kg/m^3; $P_{RO,}$ the unit water produced by reverse osmosis, m^3/kWh; $E_{PV\text{-}CDI}$, the unit CO_2 emission of capacitive deionization driven by photovoltaic, kg/m^3; η, the thermal efficiency of thermal power generation; f_{Thermal}, the effective CO_2 emission factor of a certain kind of fuel, kg/TJ; f_{PV}, the unit CO_2 emission of photovoltaic in life cycle, kg/kWh. For RO driven by thermal power of coal combustion, take η = [0.32,0.45], P_{RO} = [1.5,5.5] [102], f_{Thermal} = [87,300,125,000] [103], hence E_{RO} = [1.47,5.50]. And for photovoltaic powered capacitive deionization, take P_{CDI} = [0.3,6] [104] and f_{PV} = [0.093,0.098] [105], hence $E_{PV\text{-}CDI}$ = [0.03,0.59], that is, at least 0.88 Kg CO_2 emission per cubic meter can be reduced by using PV powered CDI than traditional fuel driven reverse osmosis, let alone some energy-intensive technologies like multi-stage flash (MSF) and multi-effect distillation (MED). This rough conversion from product water to CO_2 emission implied, the potential of clean energy driven desalination cannot be underestimated.

The construction of CEDI system will bring a chance of increasing irrigation water in the study area. Evaluation of different CEDI technology portfolios is crucial to the system design and parameter optimization of CEDI system in the future. This study evaluated six alternatives of potential and offered the most suitable technology portfolio coupling photovoltaic, capacitive deionization and alternating brackish-irrigation water resources (PCA) for use in the study area. PCA is very promising in the study area for the rich brackish water resources and solar resources. Photovoltaic power generation facilities are common in the research area, with an installed capacity of 10.216 million kilowatts. And previous studies showed brackish water irrigation with appropriate irrigation management is proved to be feasible for cottons in Xinjiang, which is of high economic value. For low molar concentration streams like brackish water, CDI is a promising alternative to expensive and energy-intensive technologies such as reverse osmosis [98].

However, the promotion of this system in large scale may still encounter the following obstacles. Firstly, the CDI technology has not yet become a mature commercial technology, technological advances and cost reductions need to be achieved to realize large-scale applications. Secondly, despite the large installed capacity of photovoltaic power generation in Xinjiang, it only accounts for 11.7% of Xinjiang's electricity power grid, proving more work and incentives need to be done to achieve further promotion of photovoltaics. Thirdly, alternating brackish-freshwater irrigation with inappropriate managements will cause soil salinization and serious yield shrink. Hence irrigation experiments on a field scale need to be done before applying this system in largescale. For local farmers, the investment of CEDI system, which include the desalination, irrigation, power generation equipment and so on, may be too expensive to afford, implicating policy incentives or subsidies for farmers are needed to popularize this system. Farmers should be equipped with more knowledge about irrigation and soil management to realize better food production. For policy makers, the policy that incentivizes farmers and local residents to use CEDI system should be made scientifically. Also, government should invest in projects that aims to promote CDI, PV, and drip irrigation technologies.

Technology portfolios in this study were simple combinations of technological links, deep thoughts are needed in the future to establish a system that is more similar to actual applications. The number of criteria, alternatives, and experts were limited in this study to make the work manageable, leading to insufficient input data for the model. Therefore, subsequent studies should include more technological portfolios and evaluation criteria.

5. Conclusions

There is a great potential for supplementing irrigation water with desalinated brackish water by clean energies in arid and semi-arid regions. As the first step of system design, technology portfolios lay a foundation for subsequent process design and control. Therefore, screening of appropriate technology portfolios is of utmost significance for successful establishment of clean energy driven desalination-irrigation (CEDI) systems. CEDI system includes three core technology links: power generation, desalination, and irrigation. Different technology portfolios are formed by various options on each technological link, which have different economical, environmental, agricultural, and societal implications. Multi-criteria group decision-making (MCGDM) is a proper way of comprehensively evaluating the integrated performances of technology portfolios of clean energy-driven desalination-irrigation (CEDI) systems. During multi-criteria group decision-making, uncertainty arising from linguistic information and varying confidence in estimation is usually available as interval-valued intuitionistic fuzzy sets (IVIFSs). Previous studies relied on the direct provision of IVIFSs by experts, which made them inapplicable in real-world problems because experts' understanding over IVIFSs might be limited and inconsistent. Therefore, an easy-to-operate method for collection and conversion of IVIFSs was proposed in this study to avoid misunderstanding and facilitate realistic reflection of expert judgements. Duplex rating sets (DRSs) were proposed to express uncertain estimates and the associated confidence levels, and transformation equations were established to convert DRSs into IVIFSs. Based on the introduction of DRSs and transformation equations, an entropy-weighted TOPSIS approach with IVIFSs information was then developed. The weights of criteria and experts were determined according to IVIF entropies, and the ranking of alternatives were obtained by an extended TOPSIS method based on IVIF correlation measures.

In order to verify the applicability of the method, this method was applied to the assessment of technology portfolios of CEDI system in Xinjiang, a province of Northwest China. Eleven experts participated in the evaluation of six technological portfolios where six criteria were taken into account. The technology portfolio consisting of photovoltaic power generating technology, capacitive deionization desalination technology and alternating brackish-fresh water irrigation (PCA) was screened out as the most suitable one to promote in the study area. In addition, sensitivity analysis of expert weight, criteria weight, and hesitant degree parameter was conducted. The results showed PCA has significant advantage, which ranked first in 12 of total 20 settings. And it is crucial to assign weights to experts objectively.

PCA is also of potential for greenhouse effect caused by desalination. By using photovoltaic powered capacitive deionization, at least 0.88 Kg CO_2 emission per cubic meter can be reduced compared to traditional fuel driven reverse osmosis. While immaturity in CDI technologies, limited scale of photovoltaic power generation capacity, and the risk of yield shrink and soil salinization caused by using inappropriate alternating brackish-freshwater may hinder the promotion of PCA. Policies on technology advancements, subsidies for residents, and experiments of irrigation may be helpful to overcome these obstacles and promote CEDI systems in arid regions.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Abbreviations

CEDI	Clean energy-driven desalination-irrigation
FSs	Fuzzy sets
HCA	A technology portfolio of hybrid photovoltaic-wind power generation, capacitive deionization, and alternating brackish-fresh water irrigation
HCF	A technology portfolio of photovoltaic-wind power generation, capacitive deionization, and freshwater irrigation
HRF	A technology portfolio of photovoltaic-wind power generation, reverse osmosis, and freshwater irrigation
IFSs	Intuitionistic fuzzy sets
IVIFSs	Interval-valued intuitionistic fuzzy sets
MCDM	Multi-criteria decision-making
PCA	A technology portfolio of photovoltaic power generation, capacitive deionization, and alternating brackish-fresh water irrigation
PCF	A technology portfolio of photovoltaic power generation, capacitive deionization, and fresh water irrigation
PRF	A technology portfolio of photovoltaic power generation, reverse osmosis, and freshwater irrigation

CRediT authorship contribution statement

Kejia Hu: Investigation, Methodology, Formal analysis, Writing - original draft. **Qian Tan:** Conceptualization, Writing - review & editing, Funding acquisition, Supervision, Resources. **Tianyuan Zhang:** Validation. **Shuping Wang:** Visualization.

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