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Selecting renewable desalination using uncertain data: an MCDM framework combining mixed objective weighting and interval MARCOS

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ABSTRACT

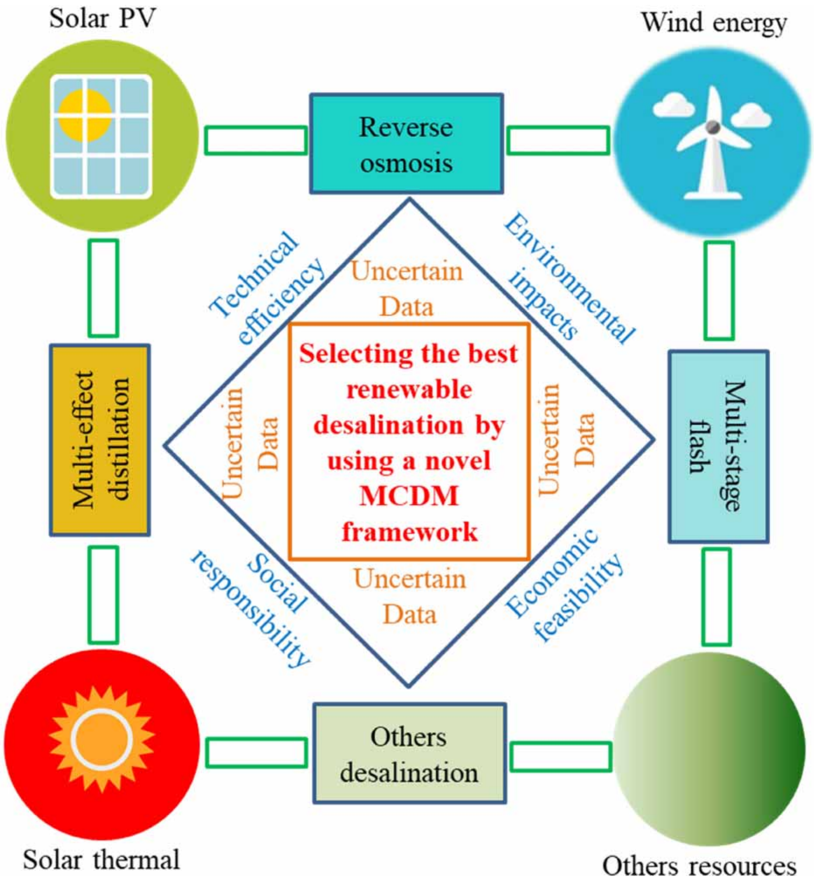
Using renewable energy to drive desalination is increasingly favored to augment water supply, given its cost advantage and energy saving. Divergent renewables can be integrated into different desalination technologies, resulting in the selection of an appropriate renewable desalination being a challenge. This work proposes a multi-criteria decision-making framework to evaluate renewable desalination alternatives from the perspective of multi-dimensional consideration and data uncertainty by developing a mixed objective weighting (MOW) method and extending the method of MARCOS (measurement of alternatives and ranking according to a compromise solution) into uncertain conditions. Mathematical contributions can be found in the two methods, i.e. the MOW improves the objectivity and fairness in the weighting result by considering the dispersions and correlations among the criteria's performances, and interval MARCOS guarantees stability in the ranking result while well preserving the uncertain data. An illustrative case concerning four renewable desalination alternatives is used to test the feasibility of the framework. After implementing comparisons regarding the weighting result and ranking sequence, the effectiveness of the involved methods is confirmed. In conclusion, by fully utilizing objective data concerning renewable desalination while eliminating subjective interference, the developed framework can offer a rational and reliable decision output.

Key words: combined objective weights, interval MARCOS, multi-criteria decision-making, renewable energy-driven desalination, uncertainty

HIGHLIGHTS

- A hybrid multi-criteria decision-making framework is used to select renewable desalination.
- A MOW method is proposed to assign the weights.
- An interval MARCOS is introduced to rank the alternatives.
- Multi-dimensional criteria system is created with consideration of uncertain data.
- Weights and sequence are generated by fully utilizing the objective data.

GRAPHICAL ABSTRACT



1. INTRODUCTION

Water shortage and energy depletion are major issues facing the world. Due to increased population, industrialization, and living standards, desalination technologies have been regarded as promising solutions for water scarcity (Benghanem *et al.* 2022). However, as energy-intensive processes, desalination technologies that are powered by fossil fuels consume plenty of power while generating a large amount of greenhouse gases (GHGs), resulting in the necessity of integrating renewable energy into desalination technologies (Tigrine *et al.* 2021).

Desalination technologies can be categorized into thermal and membrane processes. The thermal processes, like multi-effect distillation (MED) and multi-stage flash distillation (MSF), belong to the phase-change technologies, which use evaporators and condensers to generate potable water from seawater or brackish water by resorting to the vaporization principle. The membrane processes, like reverse osmosis (RO) and electrodialysis (ED), belong to the non-phase-change technologies, which employ physical barriers to separate the salts from the seawater for producing freshwater (Gude 2016). However, the membrane processes of RO and ED rely heavily on electrical power for operation, while the thermal processes of MED and MSF consume much more energy, including both thermal and electrical (Abdelkareem *et al.* 2018). The challenge highlights the necessity of developing and practicing renewable desalination systems by integrating renewable energy resources into the thermal or membrane processes. Recently, some efforts have been made in renewable desalination systems. For instance, solar collectors are used for supporting a MED plant with a capacity of 72 m^3/day, where a water production cost of US\$4.95/m^3 is achieved (Cunha & Pontes 2022). In the work of Kabiri *et al.* (2021), environmental friendliness and economic benefit have been confirmed by integrating solar thermal into the MSF technology. Solar photovoltaic (PV) instead of solar collectors is applied to power the membrane technology of RO and the result verifies both the technical and economic feasibility of the renewable desalination combination (Mostafaeipour *et al.* 2019). In the literature (Rosales-Asensio *et al.* 2019), wind power is also utilized to drive the RO process and the cost of water could be reduced by enhancing the feasibility and efficiency of this renewable desalination. Besides the above-mentioned technologies and energy resources, other desalination processes like mechanical vapor compression (MVC) (Tzen 2018), ED reversal (EDR) (He *et al.* 2020), humidification dehumidification (HDH) (He *et al.* 2022), as well as other powers such as geothermal (Behnam *et al.* 2022) and wave energy (Brodersen *et al.* 2022) could be integrated into renewable desalination systems.

Given those varieties of desalination technologies could be powered by different renewable energy resources, how to identify the most appropriate renewable desalination among multiple alternatives becomes a challenging task. Appropriate renewable desalination should consider several aspects, including technological efficiency, environmental impacts, economic feasibility, and social responsibility. Consequently, the overall performance of renewable desalination is better defined using multi-dimensional criteria, which results in the necessity of applying multi-criteria decision-making (MCDM) in the identification. As summarized in Table 1, the feasibility of the application of MCDM in renewable desalination systems has been confirmed by several studies.

As observed in Table 1, when selecting appropriate renewable energy, multiple criteria should be considered. Since the relative importance regarding each assessment criterion is associated with the contribution of the criterion to the overall performance of

Table 1 | Literature regarding renewable desalination selection using MCDM

Reference	No. of criteria	Data feature	Weighting method	Ranking method	Uncertain	Method feature
Huang (2022)	8	Qualitative and quantitative	Entropy	VIKOR	Interval numbers	Entropy is an objective weighting method that assigns the weights according to the data variations; VIKOR is a compromise ranking method that integrates maximum group utility and minimal individual regret for ranking the alternatives.
Xu *et al.* (2020b)	10	Qualitative and quantitative	DANP	VATOPSIS	Interval numbers	DANP is a subjective weighting method that clarifies the criteria's interrelationships using experts' judgment; VATOPSIS is a modified compromise ranking method that considers the ideal and anti-ideal solutions using vector function.
Dsilva Winfred Rufuss *et al.* (2018)	6	Quantitative	AHP	DEA	Fuzziness in human judgments	AHP is a subjective weighting method that uses human preferences pair-wisely; DEA compares the efficiency of the alternatives by converting inputs into outputs.
Marini *et al.* (2017)	33	Quantitative	Scaling method	WSM	Not considered	Scaling method is a subjective weighting method that directly assigns scales to the criteria; WSM is the simplest compensatory ranking method using the aggregation function.
Georgiou *et al.* (2015)	18	Qualitative and quantitative	AHP	PROMETHEE	Not considered	AHP is a pair-wise subjective weighting method; PROMETHEE is a non-compensatory method that compares the alternatives by creating the outranking relations.
Kondili *et al.* (2013)	18	Quantitative	Pair-wise comparison	WSM	Not considered	Like AHP, pair-wise comparison is a subjective weighting method; WSM is a simple ranking method.
Liu *et al.* (2013)	13	Quantitative	AHP	WSM	Fuzziness in human judgments	AHP is a pair-wise subjective weighting method; WSM is a simple ranking method.
Rújula & Dia (2010)	5	Qualitative and quantitative	Multi-attribute analysis	–	Not considered	Multi-attribute analysis enables users to manage multiple conflict criteria simultaneously.

renewable desalination, adopting a proper weighting method plays a critical role in generating a rational decision output. Based on the collected data of the criteria and the determined weights, different ranking techniques can be utilized in prioritizing renewable desalination alternatives. However, it is hard to tell which method is better because different ranking methods with divergent computational mechanisms will generate discrepant results. As also observed in Table 1, the quality of the evaluation data used in the decision-making could be improved. On the one side, quantitative information cannot avoid excessive disturbance from subjective factors; on the other side, because of many uncertainties (Skourtos *et al.* 2021) qualitative data are always volatile rather than deterministic. Therefore, to better use the uncertain data from the multi-dimensional criteria in renewable desalination selection, two mathematical limitations need to be addressed, as specified below.

The first limitation is the lack of a rational method to grant objectivity and fairness to the weighting result. Specifically, pairwise comparisons (like AHP) are the most frequently adopted weighting methods, which determine the relative importance of the criteria according to subjective preferences. However, by heavily relying on the users' experiences, the subjective weights would be manipulated by the users consciously or unconsciously. In contrast, objective ones (like entropy) can assign weights to the criteria by analyzing their qualitative information. With the growing number of valuable data available in renewable desalination systems, weighting the criteria objectively has been well accepted by recent literature (Rezk *et al.* 2021; Huang 2022). However, traditional objective methods assign weights by analyzing the dispersions among the evaluation data, failing to consider the correlations between the interrelated criteria. As declared in Li *et al.* (2020), using multi-criteria to depict the overall performance of energy-related systems is challenging because the involved criteria could have complex interrelationships; more importantly, ignoring the interrelationships would lead to a biased weighting result (Xu *et al.* 2020b).

The second limitation is that the ranking method should be improved to ensure consistency with the uncertain data and stability in the decision output. Among the MCDM, the compensatory ranking approaches, especially TOPSIS (technique for order of preference by similarity to ideal solution) and its variations, have been quite favored in previous work regarding desalination systems (Vivekh *et al.* 2017; Wang *et al.* 2019; Xu *et al.* 2020b), since they can consider both the best and the worst scenarios in the decision issues and thus offer a complete ranking result by analyzing the weighted evaluation data. However, when the number of criteria and alternatives grows, the evaluation data become complex because of uncertainty, which may increase the sensitivity and instability of the ranking results caused by the fluctuations in weights and performance ratings in the criteria (Trung 2022).

This study proposes a generic mathematical framework in renewable desalination selection to upgrade the weighting and ranking technique under uncertain data conditions by introducing a novel mixed objective weighting (MOW) method and extending a ranking technique. To improve the objectiveness and fairness in the weighting result, the MOW combines the variations and correlations among the performance ratings of the criteria. In this method, on the one side, the dispersion regarding the criteria is measured by using interval MEREC (method based on the removal effects of criteria), which assigns a greater dispersion level to a criterion when its removal leads to more impact on the overall performance (Keshavarz-Ghorabaee *et al.* 2021). On the other side, complex interrelationships among the criteria can be addressed by proposing interval GANP (grey-relational coefficient-based analytic network process), where the ANP measures the correlation degrees by resorting to the objective datasets generated by the grey relational coefficient (GRC). In addition, dispersions and correlations are integrated into the MOWs by creating a constrained optimization programming. To guarantee consistency with the uncertain data and stability in the prioritization, MARCOS (measurement of alternatives and ranking according to compromise solution), a relatively new ranking method, is extended into interval number conditions to identify the most appropriate renewable desalination. The most attractive feature of MARCOS is the ability to maintain stability in the decision output by integrating three well-recognized concepts in MCDM. Specifically, the ideal and anti-ideal reference points, relationships between the reference points and a set of alternatives, as well as the utility degree approach, are properly reconciled to guarantee the reliability of the MARCOS (Deveci *et al.* 2021; Gong *et al.* 2021). Therefore, after extending the MARCOS into uncertain conditions, massive criteria and alternatives in renewable desalination can be well evaluated. In general, the contributions of the proposed hybrid MCDM framework include:

- The MOWs are generated from the performance ratings of the criteria, which eliminate human manipulation; more importantly, by capturing and integrating both the dispersions and correlations among the numerical data, the MOW method can grant fairness and rationality in the weighting result.
- Interval MARCOS enables prioritization under uncertain conditions by fully using the evaluation data while well preserving their original uncertainties; meanwhile, this method reconciles three comparison concepts to rank the alternatives, which improves the stability and robustness of the decision output.

The rest of this work is organized as follows: Section 2 introduces the related mathematical methods, Section 3 uses a case study to test the feasibility of the framework, Section 4 provides the results comparison, and Section 5 offers the conclusions and future directions.

2. METHODS

The hybrid MCDM framework is depicted in Figure 1, which comprises the MOW method for determining the weights and interval MARCOS for ranking the alternatives. Notably, the weighting and ranking methods are combined with interval numbers to address uncertainty issues in real-world decisions. Compared with previous work, this MCDM framework only uses collected data regarding the performance ratings of the criteria to evaluate renewable desalination alternatives, which offers an objective decision that avoids subjective human manipulation. The framework assumes there are m alternatives that need to be compared by using n criteria and the original data of the ith alternative regarding the jth criterion is $[z_{ij}^{L}, z_{ij}^{U}]$, where 'L' and 'U' signify 'lower' and 'upper' limits of an interval, respectively. The operational laws regarding the interval numbers are offered in Supplementary Table A1.

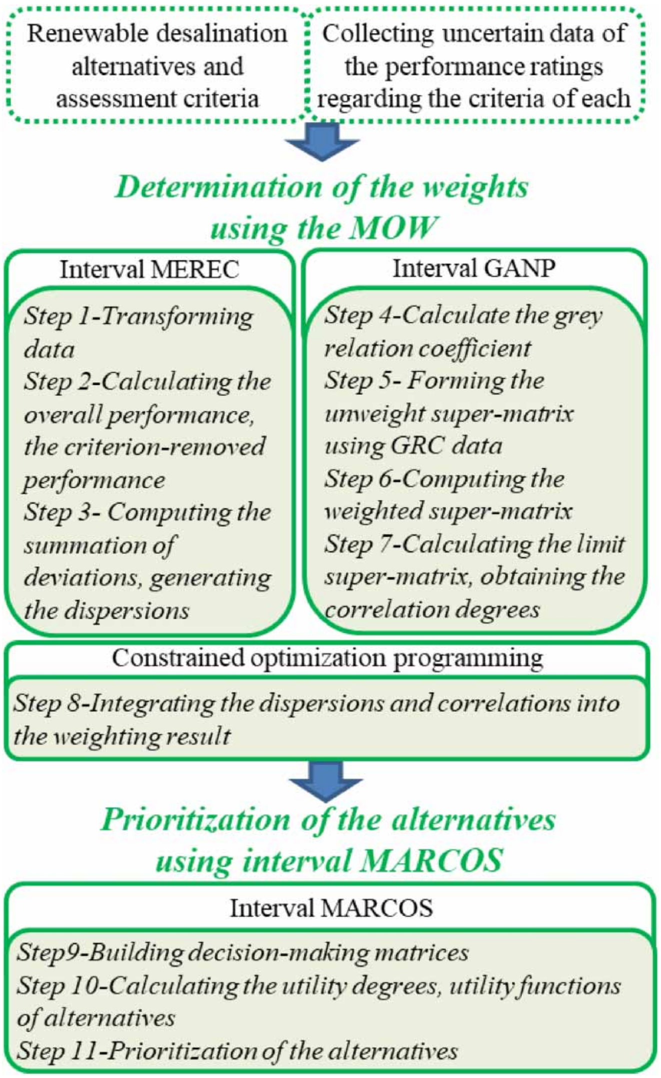


Figure 1 | MCDM framework for renewable desalination selection.

2.1. Mixed objective weighting

Eight steps are involved in the MOW method. Interval MEREC (Steps 1–3) calculates the dispersion of the criteria, interval GANP (Steps 4–7) obtains the correlations between the criteria and constrained optimization programming (Step 8) integrates the dispersions and the correlations into the objective weighting.

2.1.1. Interval MEREC for calculating the dispersions

MEREC fully utilizes the performance ratings of the criteria and thus offers a rational way to measure their variations and dispersions. Considering the uncertain feature of the evaluation data, the traditional MEREC (Keshavarz-Ghorabaee *et al.* 2021) is extended into the interval number conditions for measuring the dispersion levels among the criteria, via the following actions.

Step 1: Transforming data. The original collected data of the criteria's performance ratings should be transformed using Equation (1). Notably, different transforming formulas are needed according to the benefit or cost feature of a certain criterion.

Step 2: Calculating the overall performance and the criterion-removed performance. First, a logarithmic measurement (Equation (2)) is used to calculate the alternative's overall performance. Subsequently, a similar measurement (Equation (3)) determines the criterion-removed performance. Compared with Equation (2), the performance calculated by Equation (3) is based on removing each criterion separately (Keshavarz-Ghorabaee *et al.* 2021).

Step 3: Computing the summation of deviations and generating the dispersions. This step uses Equation (4) to analyze the removal effect by aggregating the deviations among the values derived from Step 2. Subsequently, the removal effects are utilized to measure the dispersions among the criteria, as given in Equation (5).

$$\begin{cases} [\bar{z}_{ij}^L, \bar{z}_{ij}^U] = \left[\dfrac{\min\limits_i (z_{ij}^L)}{z_{ij}^U}, \dfrac{\min\limits_i (z_{ij}^L)}{z_{ij}^L}\right], \text{where the } j\text{th criterion is a benefit criterion} \\ [\bar{z}_{ij}^L, \bar{z}_{ij}^U] = \left[\dfrac{z_{ij}^L}{\max\limits_i (z_{ij}^U)}, \dfrac{z_{ij}^U}{\max\limits_i (z_{ij}^U)}\right], \text{where the } j\text{th criterion is a cost criterion} \end{cases} \tag{1}$$

$$[S_i^L, S_i^U] = \left[\ln\left\{1 + \left[\frac{1}{m}\sum_j |\ln(\bar{z}_{ij}^U)|\right]\right\}, \ln\left\{1 + \left[\frac{1}{m}\sum_j |\ln(\bar{z}_{ij}^L)|\right]\right\}\right] \tag{2}$$

$$[S_{ij}^L, S_{ij}^U] = \left[\ln\left\{1 + \left[\frac{1}{m}\sum_{k,k\neq j} |\ln(\bar{z}_{ik}^U)|\right]\right\}, \ln\left\{1 + \left[\frac{1}{m}\sum_{k,k\neq j} |\ln(\bar{z}_{ik}^L)|\right]\right\}\right] \tag{3}$$

$$[E_j^L, E_j^U] = [S_{ij}^L - S_i^U, S_{ij}^U - S_i^L] \tag{4}$$

$$[wd_j^L, wd_j^U] = \left[\frac{E_j^L}{\frac{1}{2}\left(\sum_j E_j^L + \sum_j E_j^U\right)}, \frac{E_j^U}{\frac{1}{2}\left(\sum_j E_j^L + \sum_j E_j^U\right)}\right] \tag{5}$$

2.1.2. Interval GANP for calculating the correlations

ANP has been widely practiced for analyzing interrelated criteria. However, the initial relationships in ANP are created based on subjective assumptions, failing to offer an objective way to calculate the inherent correlations. This work introduces a novel technique by combining the grey relational coefficient (GRC) with the ANP, where the GRC is used to provide the statistic-based relationships and enables the ANP to determine the correlations objectively. The introduced GANP includes four steps, which are also implemented under uncertain conditions.

Step 4: Calculating the grey relational coefficient. This step applies the GRC under interval number conditions to obtain the initial relationships among the criteria. By referring to the literature (Li *et al.* 2020), the reference performance is set as $([\bar{z}_{1j}^L, \bar{z}_{1j}^U], [\bar{z}_{2j}^L, \bar{z}_{2j}^U], \ldots, [\bar{z}_{mj}^L, \bar{z}_{mj}^U])$ and the comparing performance is determined as $([\bar{z}_{1k}^L, \bar{z}_{1k}^U], [\bar{z}_{2k}^L, \bar{z}_{2k}^U], \ldots, [\bar{z}_{mk}^L, \bar{z}_{mk}^U])$, where

$k \neq j$. The GRC of the jth criterion regarding the ith alternative can be obtained using Equation (6), where ρ is a distinguishing parameter and set as 0.5 according to Tseng *et al.* (2018). After summarizing the values of $[G^L_{j|k}(i), G^U_{j|k}(i)]$ among the alternatives, the required GRC regarding the jth criterion with respect to each comparison criterion is obtained by running Equation (7):

$$\begin{cases} G^L_{j|k}(i) = \min\left\{\dfrac{\min|\bar{z}^L_{ij} - \bar{z}^L_{ik}| + \rho\max|\bar{z}^L_{ij} - \bar{z}^L_{ik}|}{|\bar{z}^L_{ij} - \bar{z}^L_{ik}| + \rho\max|\bar{z}^L_{ij} - \bar{z}^L_{ik}|}, \dfrac{\min|\bar{z}^U_{ij} - \bar{x}^U_{ik}| + \rho\max|\bar{z}^U_{ij} - \bar{z}^U_{ik}|}{|\bar{z}^U_{ij} - \bar{z}^U_{ik}| + \rho\max|\bar{z}^U_{ij} - \bar{z}^U_{ik}|}\right\} \\ G^U_{j|k}(i) = \max\left\{\dfrac{\min|\bar{z}^L_{ij} - \bar{z}^L_{ik}| + \rho\max|\bar{z}^L_{ij} - \bar{z}^L_{ik}|}{|\bar{z}^L_{ij} - \bar{z}^L_{ik}| + \rho\max|\bar{z}^L_{ij} - \bar{z}^L_{ik}|}, \dfrac{\min|\bar{z}^U_{ij} - \bar{x}^U_{ik}| + \rho\max|\bar{z}^U_{ij} - \bar{z}^U_{ik}|}{|\bar{z}^U_{ij} - \bar{z}^U_{ik}| + \rho\max|\bar{z}^U_{ij} - \bar{z}^U_{ik}|}\right\} \end{cases} \quad (6)$$

$$[G^L_{jk}, G^U_{jk}] = \left[\frac{1}{i}\sum_i G^L_{j|k}(i), \frac{1}{i}\sum_i G^U_{j|k}(i)\right] \quad (7)$$

Subsequently, the value of $[G^L_{jk}, G^U_{jk}]$ is taken as original data for implementing the ANP method.

Step 5: Forming the unweighted super-matrix using GRC data. By referring to Nabeeh *et al.* (2021), the assumed relationships among the criteria in the traditional ANP are replaced by the values determined in this step, which generate the matrix of T_{I} in the proposed GANP (see Equation (8)). Notably, considering the involved interval number, all matrices in ANP should be divided into the lower matrix ($T^{\mathrm{L}}_{\mathrm{I}}$) and the upper matrix ($T^{\mathrm{U}}_{\mathrm{I}}$) for separation operations. Subsequently, the elements in T_{I} are normalized to form the unweighted super-matrix of U_{N} (see Equation (9)), by running $d^{L(U)}_i = \sum_{k=1}^{n} G^{L(U)}_{ik}$, where 'L(U)' signifies 'L or U respectively'.

$$T^{\mathrm{L(U)}}_{\mathrm{I}} = \begin{bmatrix} G^{L(U)}_{11} & \cdots & G^{L(U)}_{1k} & \cdots & G^{L(U)}_{1n} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ G^{L(U)}_{i1} & \cdots & G^{L(U)}_{ik} & \cdots & G^{L(U)}_{in} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ G^{L(U)}_{n1} & \cdots & G^{L(U)}_{nk} & \cdots & G^{L(U)}_{nn} \end{bmatrix} \quad (8)$$

$$U^{\mathrm{L(U)}}_{\mathrm{N}} = \begin{bmatrix} G^{L(U)}_{11}/d_1 & \cdots & G^{L(U)}_{1k}/d_1 & \cdots & G^{L(U)}_{1n}/d_1 \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ G^{L(U)}_{i1}/d_i & \cdots & G^{L(U)}_{ik}/d_i & \cdots & G^{L(U)}_{in}/d_i \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ G^{L(U)}_{n1}/d_n & \cdots & G^{L(U)}_{nk}/d_n & \cdots & G^{L(U)}_{nn}/d_n \end{bmatrix} = \begin{bmatrix} r^{L(U)}_{11} & \cdots & r^{L(U)}_{1k} & \cdots & r^{L(U)}_{1n} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ r^{L(U)}_{i1} & \cdots & r^{L(U)}_{ik} & \cdots & r^{L(U)}_{in} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ r^{L(U)}_{n1} & \cdots & r^{L(U)}_{nk} & \cdots & r^{L(U)}_{nn} \end{bmatrix} \quad (9)$$

Step 6: Computing the weighted super-matrix. After transposing the matrix of U_{N} by running Equation (10), the weighted super-matrix can be determined, as given in Equation (11):

$$(U^{\mathrm{L(U)}})^{\mathrm{trans}} = \begin{bmatrix} r^{L(U)}_{11} & \cdots & r^{L(U)}_{i1} & \cdots & r^{L(U)}_{n1} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ r^{L(U)}_{1k} & \cdots & r^{L(U)}_{ik} & \cdots & r^{L(U)}_{nk} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ r^{L(U)}_{1n} & \cdots & r^{L(U)}_{in} & \cdots & r^{L(U)}_{nn} \end{bmatrix} = \begin{bmatrix} u^{L(U)}_{11} & \cdots & u^{L(U)}_{i1} & \cdots & u^{L(U)}_{n1} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ u^{L(U)}_{1k} & \cdots & u^{L(U)}_{ik} & \cdots & u^{L(U)}_{nk} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ u^{L(U)}_{1n} & \cdots & u^{L(U)}_{in} & \cdots & u^{L(U)}_{nn} \end{bmatrix} \quad (10)$$

$$V^{L(U)} = \begin{bmatrix} r^{L(U)}_{11} \times u^{L(U)}_{11} & \cdots & r^{L(U)}_{1k} \times u^{L(U)}_{i1} & \cdots & r^{L(U)}_{1n} \times u^{L(U)}_{n1} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ r^{L(U)}_{i1} \times u^{L(U)}_{1k} & \cdots & r^{L(U)}_{ik} \times u^{L(U)}_{ik} & \cdots & r^{L(U)}_{in} \times u^{L(U)}_{nk} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ r^{L(U)}_{n1} \times u^{L(U)}_{1n} & \cdots & r^{L(U)}_{nk} \times u^{L(U)}_{in} & \cdots & r^{L(U)}_{nn} \times u^{L(U)}_{nn} \end{bmatrix} \quad (11)$$

Step 7: Calculating the limit super-matrix and obtaining the correlation degrees. The weighted super-matrix is converted into the stable limit super-matrix by running Equation (12). In the matrix, every row element is equal, representing the required correlation degree of each criterion (denoted as $[wr_j^L, wr_j^U]$):

$$W^{L(U)} = \lim_{\gamma \to \infty} [V^{L(U)}]^{\gamma} = \begin{bmatrix} [wr_1^L, wr_1^U] & \cdots & [wr_1^L, wr_1^U] & \cdots & [wr_1^L, wr_1^U] \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ [wr_i^L, wr_i^U] & \cdots & [wr_i^L, wr_i^U] & \cdots & [wr_i^L, wr_i^U] \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ [wr_n^L, wr_n^U] & \cdots & [wr_n^L, wr_n^U] & \cdots & [wr_n^L, wr_n^U] \end{bmatrix} \quad (12)$$

2.1.3. Constrained optimization programming for generating the MOWs

Step 8: Integrating the dispersions and correlations into the weighting result. Both the dispersions and correlations among the criteria can be measured by using the objective evaluation data. Based on this, the MOW of each criterion is obtained by building a constrained optimization programming that depends on the Euclidean distance, as given in Equation (13) by referring to Xu *et al.* (2020a):

$$\min J = \sum_j \left[\sqrt{(w_j - wd_j^L)^2 + (w_j - wd_j^U)^2} + \sqrt{(w_j - wr_j^L)^2 + (w_j - wr_j^U)^2} \right]$$
$$\text{s.t.} \begin{cases} \sum_{j=1}^{n} w_j = 1 \\ w_j \geq \min(wd_j^L, wr_j^L) \\ w_j \leq \max(wd_j^U, wr_j^U) \end{cases} \quad (13)$$

2.2. Interval MARCOS

As a relatively new ranking method proposed by Stević *et al.* (2020), MARCOS belongs to the compensatory MCDM methods, which can offer a complete sequence of alternatives by resorting to the utility degree approach and the reference point sorting approach. Considering the involved uncertainty in the evaluation data, the traditional MARCOS is extended into interval number conditions for implementing the prioritization: see Steps 9–11.

Step 9: Building decision-making matrices. In this step, three decision-making matrices should be created sequentially. First, the original evaluation data are gathered for building the initial matrix (*IM*). The matrix in Equation (14) also includes two reference alternatives, i.e. the worst alternative (wz_j) and the best alternative (bz_j). Specifically, the elements in the worst and the best alternatives should be determined according to the benefit or cost nature of each criterion. For instance, the criterion of water utilization efficiency belongs to the benefit type, and then the reference elements are $wz_j = \min_i z_{ij}^L$ and $bz_j = \max_i z_{ij}^U$. By contrast, for a cost criterion (like water production cost), the corresponding elements should be $wz_{j'} = \max_i z_{ij'}^U$ and $bz_{j'} = \min_i z_{ij'}^L$. Based on the dataset in *IM*, the normalized version (*NM* in Equation (15)) can be determined by running $[y_{ij}^L, y_{ij}^U] = \left[z_{ij}^L/bz_j, z_{ij}^U/bz_j\right]$ if the jth criterion belongs to the benefit type and $[y_{ij'}^L, y_{ij'}^U] = \left[bz_{j'}/z_{ij'}^U, bz_{j'}/z_{ij'}^L\right]$ if the jth criterion is a cost one. Finally, the weighted decision-making matrix (*WM*) is offered in Equation (16) by combining the elements in *NM* with the MOWs, that is $[t_{ij}^L, t_{ij}^U] = [w_j \times y_{ij}^L, w_j \times y_{ij}^U]$.

$$IM = \begin{bmatrix} wz_1 & wz_2 & \cdots & wz_n \\ [z_{11}^L, z_{11}^U] & [z_{12}^L, z_{12}^U] & \cdots & [z_{1n}^L, z_{1n}^U] \\ [z_{21}^L, z_{21}^U] & [z_{22}^L, z_{22}^U] & \cdots & [z_{2n}^L, z_{2n}^U] \\ \vdots & \vdots & \ddots & \vdots \\ [z_{m1}^L, z_{m1}^U] & [z_{m2}^L, z_{m2}^U] & \cdots & [z_{mn}^L, z_{mn}^U] \\ bz_1 & bz_2 & \cdots & bz_n \end{bmatrix} \quad (14)$$

$$NM = \begin{bmatrix} wy_1 & wy_2 & \cdots & wy_n \\ [y_{11}^L, y_{11}^U] & [y_{12}^L, y_{12}^U] & \cdots & [y_{1n}^L, y_{1n}^U] \\ [y_{21}^L, y_{21}^U] & [y_{22}^L, y_{22}^U] & \cdots & [y_{2n}^L, y_{2n}^U] \\ \vdots & \vdots & \ddots & \vdots \\ [y_{m1}^L, y_{m1}^U] & [y_{m2}^L, y_{m2}^U] & \cdots & [y_{mn}^L, y_{mn}^U] \\ by_1 & by_2 & \cdots & by_n \end{bmatrix} \quad (15)$$

$$WM = \begin{bmatrix} wt_1 & wt_2 & \cdots & wt_n \\ [t_{11}^L, t_{11}^U] & [t_{12}^L, t_{12}^U] & \cdots & [t_{1n}^L, t_{1n}^U] \\ [t_{21}^L, t_{21}^U] & [t_{22}^L, t_{22}^U] & \cdots & [t_{2n}^L, t_{2n}^U] \\ \vdots & \vdots & \ddots & \vdots \\ [t_{m1}^L, t_{m1}^U] & [t_{m2}^L, t_{m2}^U] & \cdots & [t_{mn}^L, t_{mn}^U] \\ bt_1 & bt_2 & \cdots & bt_n \end{bmatrix} \quad (16)$$

Step 10: Calculating the utility degrees and utility functions of alternatives. The utility degree of the ith alternative regarding the worst (or best) reference alternative can be determined by running Equation (17) (or Equation (18)). Subsequently, the utility function of the alternative is calculated by using Equation (19), where $f(Q_i^L) = f(Q_i^U) = P_i^L/(Q_i^L + P_i^L) = P_i^U/(Q_i^U + P_i^U)$ and $f(P_i^L) = f(P_i^U) = Q_i^L/(Q_i^L + P_i^L) = Q_i^U/(Q_i^U + P_i^U)$.

$$[P_i^L, P_i^U] = \left[\frac{\sum_j t_{ij}^L}{\sum_j wt_j}, \frac{\sum_j t_{ij}^U}{\sum_j wt_j}\right] \quad (17)$$

$$[Q_i^L, Q_i^U] = \left[\frac{\sum_j t_{ij}^L}{\sum_j bt_j}, \frac{\sum_j t_{ij}^U}{\sum_j bt_j}\right] \quad (18)$$

$$[F_i^L, F_i^U] = \left[\frac{Q_i^L + P_i^L}{1 + \frac{1 - f(Q_i^L)}{f(Q_i^L)} + \frac{1 - f(P_i^L)}{f(P_i^L)}}, \frac{Q_i^U + P_i^U}{1 + \frac{1 - f(Q_i^U)}{f(Q_i^U)} + \frac{1 - f(P_i^U)}{f(P_i^U)}}\right] \quad (19)$$

Step 11: Prioritization of the alternatives. Since the value of $[F_i^L, F_i^U]$is still in the form of an interval number, a possibility measurement (Xu & Da 2002) is applied in the comparison. For instance, two interval numbers $[F_i^L, F_i^U]$ and $[F_j^L, F_j^U]$ can be compared pair-wise by using Equation (20) where $P_{ij} > 0.5$ signifies that the value of $[F_i^L, F_i^U]$ is larger than that of $[F_j^L, F_j^U]$. Subsequently, after running Equation (20) for all the pairs of involved interval numbers, a ranking matrix can be created in Equation (21). Finally, the row elements in the ranking matrix are utilized to generate the final sequence of the alternatives by applying Equation (22), in which a higher value in FS_i means a better option.

$$P_{ij} = \max\left\{1 - \max\left(\frac{F_j^U - F_i^L}{F_j^U - F_j^L + F_i^U - F_i^L}, 0\right), 0\right\} \quad (20)$$

$$\begin{vmatrix} P_{11} & P_{12} & \cdots & P_{1m} \\ P_{21} & P_{22} & \cdots & P_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ P_{m1} & P_{m2} & \cdots & P_{mm} \end{vmatrix} \quad (21)$$

$$FS_i = \frac{\left(\sum_{j=1}^{m} P_{ij} + 0.5m - 1\right)}{m(m-1)} \quad (22)$$

3. CASE STUDY

A hybrid MCDM framework is developed in this study for evaluating renewable desalination. In this section, an illustrative case is investigated to test the feasibility of the framework. To be specific, this case study includes four alternatives and they are solar thermal-multi-stage flash (A1), solar thermal-MED (A2), photovoltaic-RO (A3), and wind power-RO (A4). Notably, the involved alternatives are applied for the framework demonstration. Users can add new alternatives or delete the original ones when applying the MCDM framework according to their research purpose. For more information regarding the alternatives, reference can be made to the literature (Abdelkareem *et al.* 2018; Xu *et al.* 2020b).

The overall performance of the alternatives is defined by an eight-criteria system that considers four dimensions. As shown in Table 2, the categorized feature regarding each dimension is depicted by two criteria, which could be either benefit criteria or cost criteria. Similarly, the evaluation criteria system could be freely created by users based on the actual conditions of the investigated alternatives and the stakeholders' interests. For being in line with the real-world decision issues, the evaluation data regarding the criteria are denoted as interval values, as shown in Table 3.

3.1. The MOWs in the case study

The relative importance of each criterion is calculated by using the MOW method. Based on the dataset in Table 3, intervals MEREC and GANP are, respectively, utilized to measure the dispersions and the correlations of the criteria. More specifically, to illustrate the procedures of interval MEREC, Supplementary Tables A2–A4 offer the transformed data (Step 1), the overall performance and the criterion-removed performance (Step 2), the summation of deviations and the obtained dispersions (Step 3). In Figure 2, the generated dispersions of the eight criteria are depicted. Meanwhile, the computational procedures of interval GANP are specified in Supplementary Tables A5–A8, including interval GRC (Step 4), the unweighted super-matrix (Step 5), the weighted super-matrix (Step 6), and the limit super-matrix (Step 7). According to the elements in the limit super-matrix, the correlations of the criteria can be determined, as shown in Figure 2. Subsequently, the MOW regarding each criterion can be determined by creating the constrained optimization programming (Equation (23)). The solution to the programming problem is obtained by using LINGO (commercial software). As given in Figure 3, two environmental criteria have greater weights than the others, while two technical criteria would contribute less to the overall performance of

Table 2 | Assessment criteria in the case study

Criterion	Unit	Dimension	Abbreviation	Type
Climate change	$kgCO_2/m^3$ H_2O	Environmental	C1	Cost
Water-using efficiency	%	Environmental	C2	Benefit
Water production cost	USD/m^3 H_2O	Economic	C3	Cost
Market share	%	Economic	C4	Benefit
Land occupation	m^2 $land/m^3$ H_2O	Social	C5	Cost
Inherent safety	score	Social	C6	Cost
Energy consumption	kWh/m^3 H_2O	Technical	C7	Cost
Life time	year	Technical	C8	Benefit

Table 3 | Collected evaluation data in the case study (Xu *et al.* 2020b; Huang 2022)

	C1	C2	C3	C4	C5	C6	C7	C8
A1	[10.915, 11.027]	[12, 15]	[1.0, 5.0]	[5.4, 6.6]	[4.78, 5.50]	[10, 12]	[3.9, 6.1]	[20, 30]
A2	[8,164, 8.260]	[15, 40]	[2.3, 2.9]	[11.7, 14.3]	[4.71, 7.39]	[14, 16]	[2.7, 4.2]	[20, 30]
A3	[0.347, 0.900]	[25, 50]	[11.7, 12.6]	[28.8. 35.2]	[3.53, 5.56]	[6, 6]	[4.0, 6.0]	[15, 20]
A4	[0.117, 0.170]	[25, 50]	[6.5, 9.1]	[17.1, 20.9]	[3.79, 5.93]	[6, 7]	[4.0, 6.0]	[15, 20]

Figure 2 | Dispersions (left) and correlations (right) of the eight criteria.

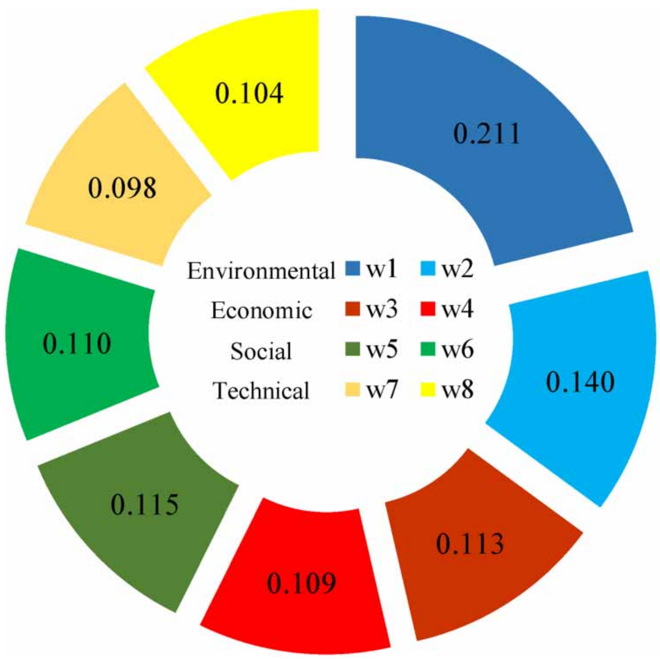


Figure 3 | Mixed objective weights of the eight criteria.

renewable desalination.

$$
\min J
$$
$$
\text{s.t.}\begin{cases} J = \sqrt{[(w1-0.073)^2+(w1-0.241)^2]} + \sqrt{[(w1-0.121)^2+(w1-0.135)^2]} + \sqrt{[(w2-0.088)^2+(w2-0.140)^2]} + \sqrt{[(w2-0.124)^2+(w2-0.136)^2]} \\ +\sqrt{[(w3-0.048)^2+(w3-0.198)^2]} + \sqrt{[(w3-0.114)^2+(w3-0.122)^2]} + \sqrt{[(w4-0.090)^2+(w4-0.159)^2]} + \sqrt{[(w4-0.128)^2+(w4-0.135)^2]}+ \\ +\sqrt{[(w5-0.105)^2+(w5-0.132)^2]} + \sqrt{[(w5-0.125)^2+(w5-0.129)^2]} + \sqrt{[(w6-0.110)^2+(w6-0.139)^2]} + \sqrt{[(w6-0.117)^2+(w6-0.133)^2]}+ \\ +\sqrt{[(w7-0.098)^2+(w7-0.140)^2]} + \sqrt{[(w7-0.118)^2+(w7-0.124)^2]} + \sqrt{[(w8-0.104)^2+(w8-0.137)^2]} + \sqrt{[(w8-0.114)^2+(w8-0.124)^2]}+ \\ w1+w2+w3+w4+w5+w6+w7+w8+w9+w10=1 \\ 0.073 \le w1 \le 0.241;\ 0.088 \le w2 \le 0.140;\ 0.048 \le w3 \le 0.198;\ 0.090 \le w4 \le 0.159; \\ 0.105 \le w5 \le 0.132;\ 0.110 \le w6 \le 0.139;\ 0.098 \le w7 \le 0.140;\ 0.104 \le w8 \le 0.137 \end{cases} \tag{23}
$$

Table 4 | Weighted matrix and the results of interval MARCOS in the case study

	C1	C2	C3	C4	C5	C6	C7	C8	$[P_i^L, P_i^U]$	$[Q_i^L, Q_i^U]$	$[F_i^L, F_i^U]$
W	0.002	0.034	0.009	0.017	0.241	0.041	0.043	0.052	1.000	0.439	0.631
A1	[0.002, 0.002]	[0.034, 0.042]	[0.023, 0.113]	[0.017, 0.020]	[0.156, 0.179]	[0.055, 0.066]	[0.043, 0.068]	[0.069, 0.104]	[0.908, 1.355]	[0.398, 0.594]	[0.500, 1.372]
A2	[0.003, 0.003]	[0.042, 0.112]	[0.039, 0.049]	[0.036, 0.044]	[0.153, 0.241]	[0.041, 0.047]	[0.063, 0.098]	[0.069, 0.104]	[1.019, 1.591]	[0.447, 0.698]	[0.661, 2.156]
A3	[0.027, 0.071]	[0.042, 0.112]	[0.009, 0.010]	[0.006, 0.007]	[0.152, 0.280]	[0.110, 0.110]	[0.044, 0.066]	[0.069, 0.104]	[1.048, 1.730]	[0.460, 0.759]	[0.708, 2.780]
A4	[0.146, 0.211]	[0.070, 0.140]	[0.012, 0.017]	[0.089, 0.109]	[0.115, 0.181]	[0.094, 0.110]	[0.044, 0.066]	[0.052, 0.069]	[1.418, 2.060]	[0.622, 0.904]	[1.555, 5.013]
B	0.211	0.140	0.113	0.109	0.115	0.110	0.098	0.104	2.279	1.000	7.472

3.2. The ranked sequence in the case study

The interval MARCOS method ranks the four renewable desalination alternatives. Specifically, the *IM*, *NM*, and the weighted matrix should be created sequentially (see Step 9). As summarized in Table 4, the weighted matrix consists of the four alternatives, as well as the worst and best ones. Subsequently, according to Step 10, the utility degree of each alternative regarding the worst ($[P_i^L, P_i^U]$) or the best ($[Q_i^L, Q_i^U]$) reference alternative is also determined, while the results are also given in Table 4. Based on this, the utility function of the *i*th alternative is calculated, as shown in the last column in Table 4.

According to Step 11, Equation (20) is implemented for comparing the value of $[F_i^L, F_i^U]$. For instance, $P_{12} = \max\{1 - \max(F_2^U - F_1^L/F_2^U - F_2^L + F_1^U - F_1^L, 0), 0\} = \max\{1 - \max(0.699, 0), 0\} = 0.301$, implying that the possibility of A1 being better than A2 is 30.1%. After comparing all the pairs of interval numbers, Equation (24) is created and the final ranking regarding the four alternatives is determined as A4 > A3 > A2 > A1, signifying that the wind power-RO would be the best choice under the current assessment conditions.

$$\begin{matrix} A1 \\ A2 \\ A3 \\ A4 \end{matrix}\begin{bmatrix} 0.500 & 0.301 & 0.226 & 0.000 \\ 0.699 & 0.500 & 0.406 & 0.121 \\ 0.774 & 0.594 & 0.500 & 0.222 \\ 1.000 & 0.879 & 0.778 & 0.500 \end{bmatrix} \overset{\text{Eq.22}}{\Rightarrow} \begin{cases} FS_1 = 0.169 \\ FS_2 = 0.227 \\ FS_3 = 0.257 \\ FS_4 = 0.346 \end{cases} \tag{24}$$

4. RESULTS COMPARISONS

In this section, two comparative items are implemented to confirm the effectiveness of the introduced weighting and ranking methods.

4.1. Weighting results comparison

The adopted MOWs are the combination of the dispersion levels and the correlation degrees among the criteria. To illustrate the necessity of combination, the values determined by interval MARCOS and interval DANP are separately employed to generate the objective weights by running Equation (25). As shown in Figure 4, the dispersion-based weights, the correlation-based weights, and the MOWs are depicted together for the comparison.

$$\min J = \sum_j \left[\sqrt{(w'_j - h_j^L)^2 + (w'_j - h_j^U)^2}\right]$$
$$\text{s.t.} \begin{cases} \sum_{j=1}^{m} w'_j = 1 \\ h_j^L \le w'_j \le h_j^U \end{cases} \tag{25}$$

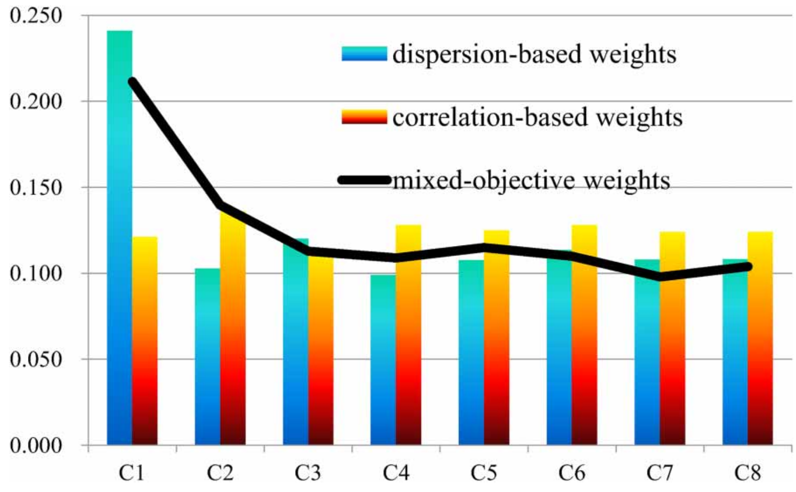


Figure 4 | Weights obtained by different methods.

In Equation (25), $[h_j^L, h_j^U]$ could be either the dispersion or the correlation regarding the jth criterion (see Figure 2) and w_j' is the corresponding dispersion-based weight or the correlation-based weight. As noted in Figure 4, the dispersion-based weights calculated by interval MARCOS are different from the correlation-based weights derived from interval DANP; while the MOW method can reconcile discrepancies in the two weights. Taking C1 as an example, it is regarded as the most important criterion (0.241) from the viewpoint of dispersion but is assigned a moderate weight (0.121) according to correlation. Meanwhile, after combining the dispersion and correlation, the MOW concerning C1 equals 0.211. Accordingly, it could be demonstrated that only taking the values generated from interval MARCOS or interval GRC would overestimate or underestimate the relative importance of the criteria, which implies the necessity for combining the dispersions and correlations into the MOWs.

4.2. Ranking results comparison

Since the utilized MARCOS is a modified ranking technique under uncertain conditions, its feasibility should be confirmed. Consequently, two well-practiced MCDM methods in their interval version are employed to prioritize the four alternatives using the same decision-making dataset. Specifically, interval TOPSIS (Jahanshahloo *et al.* 2009) and interval VIKOR (Sayadi *et al.* 2009), respectively, generate the final score of each alternative, while the sequence derived from each method can be determined by using the possibility measurement (Step 11). The ranking results are summarized in Table 5, where the top two appropriate options are the wind power-RO and the photovoltaic-RO, while the rest of the two alternatives including the solar thermal-MSF and solar thermal-MED, respectively, ranked fourth and third, signifying that combining the RO technology with renewables would be superior to the thermal-based desalination alternatives.

The feasibility of the extended interval MARCOS could be verified according to the results in Table 5. More specifically, the sequence determined by MARCOS is consistent with the TOPSIS sequence while being slightly different from result derived from the VIKOR. It is understandable since MARCOS and TOPSIS share similar ranking logic by adopting the concept of

Table 5 | Results from three interval compensatory ranking methods

	Interval MARCOS			Interval VIKOR			Interval TOPSIS		
	Final score	*FS*	Rank	Final score	*FS*	Rank	Final score	*FS*	Rank
A1	[0.500, 1.372]	0.169	4	[0.619, 1.000]	0.350	4	[0.311, 0.338]	0.100	4
A2	[0.661, 2.156]	0.227	3	[0.354, 0.901]	0.290	3	[0.389, 0.488]	0.150	3
A3	[0.708, 2.780]	0.257	2	[0.000, 0.524]	0.179	1	[0.593, 0.594]	0.210	2
A4	[1.555, 5.013]	0.346	1	[0.026, 0.525]	0.180	2	[0.572, 0.681]	0.240	1

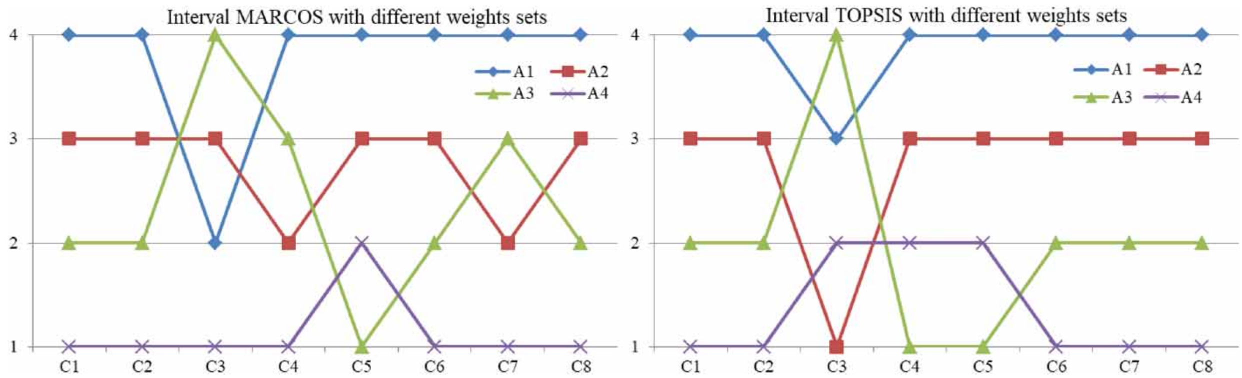


Figure 5 | Sequences determined by interval MARCOS and interval TOPSIS by using different weight sets.

ideal and anti-ideal references in the prioritization with the help of data normalization. However, VIKOR applies the concept of group utility and individual regret to rank the alternatives without data normalization. In addition, compared with TOPSIS, MARCOS additionally integrates the utility degree approach into the ranking, improving the stability of the decision output. For demonstrating stability, different weight sets are used to generate the corresponding ranking sequences, in which a dominant weight (0.3) is assigned to the jth criterion, while the other criteria weights are deemed as equal with a weight of 0.1. For instance, case C1 means the weight of C1 is 0.3 and the weights regarding C2–C8 are the same, equaling 0.1. As summarized in Figure 5, the sequences generated by MARCOS are more stable than those determined by TOPSIS, where the original best option A4 can remain the first choice in all the cases except for the case regarding the weight of $C5 = 0.3$. Consequently, it could be concluded that the extended MARCOS is suitable to be used in renewable desalination selection with the feature of enhanced stability.

5. CONCLUSIONS

Renewable desalination could benefit water supply and energy utilization, which is increasingly used to address water shortage and energy depletion. With the development of desalination technologies and renewable energy systems, using renewables to power desalination has expanded rapidly in the past decade and could be expected to increase more quickly over the coming years. Therefore, developing a systematic framework is of great significance for identifying the most appropriate renewable desalination among multiple alternatives. This study proposes an MCDM framework to assess alternatives by considering multi-dimensional criteria and uncertain data, where a novel weighting method (MOW) is introduced and a ranking method (MARCOS) is modified. In the framework, the MOW method can integrate the dispersions and correlations among the criteria to generate objective weights; interval MARCOS can be used in uncertain conditions to rank the sequence. To test the feasibility of the framework, an illustrative case concerning four renewable desalination alternatives is studied by using an eight-criteria evaluation system. In addition, the advantages and effectiveness of the involved methods are verified by comparing the results.

Compared with existing works, this study could have two mathematical contributions: on the one side, the weights of the multi-criteria are obtained by resorting to the statistical features of the evaluation data, which can avoid subjective manipulation and thus improve the weights' reliability. Notably, the MOW method combines the techniques of interval MEREC and interval GANP for simultaneously considering the dispersions and correlations among the criteria, which can offer a more rational weighting result by avoiding bias. On the other side, interval MARCOS can well preserve the original uncertainty in the evaluation data by resorting to the interval numbers. More importantly, this method adopts the utility degree approach and the reference point sorting approach to prioritize the alternatives, which can improve the stability and robustness of the decision output.

Despite the effectiveness of the proposed framework, it does have some limitations. For instance, it is suggested to use some systematic approaches to select proper criteria for building the assessment system; it needs to consider other types of uncertain data in the decision-making; and it requires providing a broader investigation by considering more desalination technologies and renewable energy resources, even including hybrid technologies and combinations between the renewables.

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DATA AVAILABILITY STATEMENT

All relevant data are included in the paper or its Supplementary Information.

CONFLICT OF INTEREST

The author declares there is no conflict.

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