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Portfolio Selection of Renewable Energy-Powered Desalination Systems with Sustainability Perspective: A Novel MADM-based Framework under Data Uncertainties

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Abstract

Harnessing renewable energy (RE) sources to power desalination systems can migrate the pressures of freshwater scarcity and fossil fuel depletion. This paper proposes a novel framework to assess the sustainability of different RE-powered desalination alternatives, by resorting to the fuzzy multi-attribute decision making (MAMD) methods. In the framework, an evaluation system that comprises ten attributes from four dimensions is introduced; while the fuzzy triangular numbers and interval values are respectively used to capture the epistemic and aleatory uncertainties. More importantly, three fuzzy MADM methods in the framework can make the following methodological contributions, i.e. fuzzy decision-making trial and evaluation laboratory-based analytic network process (DANP) offers a reliable weighting result by addressing the interrelationships among the attributes, fuzzy full consistency method (FUCOM) easily yet rigorously quantifies the qualitative attributes by using the simplest pair-wise comparison, and interval vector-aided technique for order of preference by similarity to ideal solution (VATOPSIS) generates a rational ranking sequence by integrating the absolute scores and relative balance of the multi-attributes into the prioritization. To illustrate the proposed framework, six RE-powered desalination systems were studied, showing that the solar thermal-powered multi-effect distillation would be the best option under current conditions. Besides, after conducting the results comparison and discussion, the effectiveness and advantages of the proposed framework were verified.

Keywords: Renewable energy-powered desalination; sustainability assessment; fuzzy DANP; fuzzy FUCOM; interval VATOPSIS

Abbreviations

AHP: analytic hierarchy process	BWM: best-worst method
DANP: decision-making trial and evaluation laboratory-based analytic network process	DEA: data envelop analysis
FUCOM: full consistency method	GEO-MED: geothermal powered multi-effect distillation
GRA: grey relation analysis	LCA: lifecycle assessment
MADM: multi-attributes decision making	NRM: network relation map
PV-ED: solar photovoltaic-powered electrodialysis	PV-RO: solar photovoltaic-powered reverse osmosis
RE: renewable energy	ST-MED: solar thermal powered multi-effect distillation
ST-MSF: solar thermal-powered multi-stage flash	TFN: triangular fuzzy number
(T)VC: (thermal) vapor compression	(VA)TOPSIS: (vector-aided) technique for order of preference by similarity to ideal solution
VIKOR: vlse kriterijumima optimizacija kompromiso resenje	WE-RO: wind energy-powered reverse osmosis

1. Introduction

Water scarcity always plays as a critical hinder to social and economic development. Nowadays, a total number of four billion people suffer from this issue for at least one month every year, while half a billion face it all year round (Chiavazzo et al., 2018). Converting saline water (especially seawater) into freshwater is a top priority in the strategic roadmaps in most arid or water-stressed countries/regions. Desalination technologies have been improved rapidly along with increasing water utilization over the past 50 years. According to the literature (Jones et al., 2019), over 15000 operational desalination plants with a total capacity of 95 million cubic meters per day (m^3/d) can be found on Earth at the end of 2018. In these plants, reverse osmosis (RO), multi-stage flash distillation (MSF), multi-effect distillation (MED), and electrodialysis (ED) are the top four options, accounting for 65%, 21%, 7%, and 3% of the current manufacturing capacity, respectively (Abdelkareem et al., 2018). However, these technologies consume considerable energy, for instance, the membrane-based processes of RO and ED rely on plenty of electricity for the operation, while the thermal-based MSF and MED consume much more energy including both thermal and electrical power (Abdelkareem et al., 2018). When taking fossil fuels as energy-providers, desalination plants are constrained by the depletion of conventional resources, air pollution, and the high cost of energy generation (Ramirez et al., 2019; Uche et al., 2019).

Abundant cheap and clean renewable energy sources, i.e. sunlight, wind, geothermal heat, and wave or tidal energy, provide the desalination a sustainable power, see **Figure 1** (Abdelkareem et al., 2018). For instance, Al-Othman et al. (2018) proposed a novel MSF desalination process powered by the solar thermal energy by using parabolic trough collectors and a solar pond, aiming at producing 1880 m^3/day freshwater. Mostafaeipour et al. (2019) proved that a photovoltaic (PV)-based RO desalination system could be technically and economically feasible, where a potable water capacity ranges from 148 to 228 m^3/day can be obtained with a cost of 3.02-1.96\$/m^3. Wu et al. (2018) introduced a PV/diesel driven RO desalination system for remote areas, with a cost of 1.59-2.39 \$/m^3 and a levelized cost of energy of 0.3975-0.5975 \$/kWh. Christ et al. (2017) implemented a techno-economic analysis regarding a low-enthalpy geothermal powered-MED process, showing that this integration could offer a viable freshwater supply solution with a small environmental footprint. Rosales-Asensio et al. (2019) analyzed an existing wind-powered RO desalination scheme, implying that the water production cost can be lowered through restrained capital expenses. Ylanen and Lampinen (2014) investigated a tidal energy-driven RO system by optimizing the operation pressure, which enables the economical operation while ensuring safe operation for the whole system. Zhang et al. (2018) introduce a hybrid RO desalination plant driven by solar and wind energy, and investigated the possibilities of three autonomous scenarios including wind/battery/RO, solar/battery/RO, and solar/wind/battery/RO.

Different RE-powered desalination systems have different advantages and limitations, making it necessary to identify the best system among multiple alternatives. Recently, Ben-Mansour et al. (2019) conducted an economic comparison between two promising desalination systems, indicating that wind-RO requires fewer costs than PV-RO. Raluy et al. (2005) used the life cycle assessment (LCA) to compare several desalination technologies, i.e. MED, MSF, RO integrated with solar thermal, PV, wind, hydropower, and nuclear energy, showing that integrating wind power into the desalination provokes the highest reduction in CO_2, NO_x, and SO_x emissions. Maleki (2018) introduced an improved bee algorithm for the optimization of hybrid solar/wind/battery/hydrogen/RO desalination systems, while Peng et al. (2018) used evolutionary algorithms for optimally sizing the hybrid renewable energy-powered desalination system. Al-Karaghouli and Kazmerski (2013) made a techno-economic comparison of multiple novel desalination alternatives powered by solar thermal, PV, wind, or geothermal energy, demonstrating that PV-ED shows great potential in energy saving while the solar pond-RO requires fewer costs.

The published studies compared the RE-powered desalination alternatives on environmental impacts or technical/economic performances, revealing that no existing system can lead in all aspects. Therefore, it is difficult for decision-makers/stakeholders to identify the best desalination system among multiple options. For addressing this challenge, multi-attribute decision-making (MADM) could be used to rank the alternatives according to their categorized performances. Recently, several works made contributions to the use of MADM methods to assess the sustainability of desalination systems (see **Table 1**). For instance, Ibrahim et al. (2018) created a comprehensive evaluation system for the sustainability assessment of desalination alternatives, by considering sixteen attributes from environmental, economic, social, and technical concerns. Ghassemi and Danesh (2013) combined two MADM methods to rank desalination processes, where analytic hierarchy process (AHP) was used to assign the weights to the attributes, and technique for order of preference by similarity to ideal solution (TOPSIS) was utilized to determine the sequence of the processes. Wang et al. (2019) integrated the interval numbers into MADM methods to deal with data uncertainties in the decision-making, where the interval numbers could capture both fluctuations of the numerical data and fuzziness of the human judgments. Notably, the majority of the existing works employed hybrid MADM methods in the sustainability assessment of the desalination systems, for better realizing two interrelated objectives including weights determination of the attributes and sequences prioritization of the alternatives. As observed in **Table 1**, AHP is the most frequently used method for determining the weights, while approaches like TOPSIS, data envelop analysis (DEA), grey relation analysis (GRA), and PROMETHEE, can be applied in the prioritization.

***Table 1** here*

All the previous studies are valuable inspirations for the sustainability assessment of RE-powered desalination systems. However, there are still three essential issues that inflect the reliability in the decision-making should be addressed, as specified below:

(1) It lacks the method to determine the weights of attributes rationally. Almost all the published works used AHP to determine the weights, failing to consider the interrelationships among the assessment attributes regarding the desalination systems. However, AHP determines the weights by assuming independence among the attributes, which may generate unreliable weights for the cases in which the interrelations are significant (i.e. an attribute that has more interactions with others should be assigned to a higher weight).

(2) It lacks the method to quantify the qualitative data accurately. Some previous studies used arbitrary values (like the 5-point scale) to represent the performances regarding the qualitative attributes, failing to preserve the overall consistency in the subjective judgments (Xu et al., 2017). Meanwhile, although the traditional pair-wise comparison (like AHP) quantifies the qualitative attributes with consistency thinking, it is too complicated to operate because of too many comparisons.

(3) It lacks the method to reliably prioritize the alternative systems. The traditional ranking methods (like AHP, GRA, and TOPSIS) rank the alternatives by resorting to the additional or multiplication functions to aggregate the absolute performance of each weighted attribute into the final score, failing to recognize that a real sustainable option should satisfy divergent concerns in a balanced viewpoint.

The three research gaps are critical for the sustainability assessment issues, which could become more complex under uncertain conditions. To be specific, in real desalination systems, the aleatory uncertainty in quantitative data (like the variations in water production costs), and the epistemic uncertainty in qualitative information (like the ambiguity in subjective judgments or the lack of knowledge on parameterization) cannot be ignored (Rufuss et al., 2018; Ghassemi and Danesh, 2013; Wang et al., 2019).

Therefore, this work aims at proposing a novel hybrid MADM-based decision framework for the sustainability assessment of RE-powered desalination systems, in which aleatory and epistemic uncertainties are considered. To achieve this goal, this paper integrates three fuzzy MADM methods into the decision framework, i.e. fuzzy decision-making trial and evaluation laboratory-based analytic network process (DANP) technique for the determination of the weights, fuzzy full consistency method (FUCOM) for the quantification of the qualitative information, and interval vector-aided TOPSIS (VATOPSIS) for the prioritization of the alternatives. To the best of our knowledge, this work would be the first attempt to use the MADM-based framework to assess the sustainability of RE-powered desalination systems under data uncertainties; compared to the previous studies, this work could make the following methodological contributions: (1). the suggested fuzzy DANP clarifies the interrelationships among the multi-attributes according to the ambiguous subjective judgments, which could generate a rational weighting result; (2). the extended fuzzy FUCOM quantifies the qualitative performances in an easy yet consistent way, which could offer reliable data regarding the qualitative attributes; (3). the introduced interval VATOPSIS prioritizes the alternatives in a compromise way with the consideration of both absolute score and relative balance, which could provide a rigorous ranking sequence in the context of sustainability.

Besides the introduction, the remaining parts of this work were organized as: section 2 interpreted the involved MADM approaches and the overall framework; section 3 conducted a case study; section 4 discussed the results of the case study; section 5 provided the theoretical and practical implications; while section 6 offered the conclusion and further direction of this study.

2. Mathematical framework

This work uses three MADM approaches including fuzzy DANP, fuzzy FUCOM, and interval VATOPSIS to build the decision framework under uncertainty. This segment interprets the advantages and operations of the three MADM approaches, and then offers the overall framework.

2.1 Description of the decision-making environment

The decision-making environment for actual desalination systems is uncertain (Rufuss et al., 2018; Ghassemi and Danesh, 2013; Wang et al., 2019), where both the aleatory uncertainty in the quantitative data, and the epistemic uncertainty in the qualitative information should be considered. For dealing with this issue, interval numbers and linguistic terms (corresponding to the triangular fuzzy numbers) are incorporated into the decision framework, where the former one is consistent with the nature of the variations in objective data, while the latter one allows the users to describe their judgments using natural languages while preserving ambiguities. In the framework, linguistic terms (corresponding to the TFNs) are combined with the DANP and FUCOM for assigning the weights and scoring the subjective attributes, respectively, where the epistemic uncertainty in both of the two procedures can be addressed instantly after defuzzification using Eq. 1 (Xu et al. 2018a). Besides, the interval numbers are incorporated into the VATOPSIS for representing the aleatory uncertainty when ranking the alternatives, where the aleatory uncertainty can be preserved thoroughly until the end of prioritization (Wang et al. 2019), offering a more realistic decision-making result. The operational laws regarding the interval numbers and the TFNs are summarized in **Table A1** in ***Appendix***.

$$DF\left(\tilde{a}\right)=\frac{a^{l}+4a^{m}+a^{u}}{6} \tag{1}$$

where DF refers to the defuzzification by using the graded mean integration (Guo and Zhao, 2017), $\tilde{a}=\left(a^{l},a^{m},a^{u}\right)$ is a TFN, and $a^{l}\leq a^{m}\leq a^{u}$.

2.2 Description of the fuzzy DANP

The attributes' weights influence the decision-making result. As observed in **Table 1**, previous works usually relied on AHP for determining the weights because of its advantage of preservation of consistency in subjective judgments. However, AHP ignores the interrelationships among the evaluation system, which may generate irrational weights for the cases involving interrelated attributes. As stated before, some attributes in the desalination systems can influence and be influenced by others; i.e., energy consumption (in technical dimension) would affect climate change (in environmental dimension) and water production costs (in economic dimension). Therefore, the interrelationships among the attributes are considered for the first time when assigning the weights in the desalination systems, by resorting to a hybrid method of DEMATEL-based ANP (DANP). In which, ANP assigns the weights to the interrelated attributes by creating a network structure (**Figure 2b**) instead of the AHP's hierarchical structure (**Figure 2a**). However, such an assumed network (in ANP) is too arbitrary to get reliable weights, meanwhile, it suffers from the computational difficulty for relying on too many pair-wise comparisons (Golcuk and Baykasoglu, 2016). Therefore, DEMATEL, as an effective tool for measuring the causal-effect chain components of a complex issue, has been incorporated into the ANP method for offering a reliable relationship (**Figure 2c**) instead of the assumed network (in ANP); besides, using the DEMATEL-generated matrix to replace the pair-wise comparisons can address the computational difficulty in ANP. Considering the epistemic uncertainty, a fuzzy version of DANP (Chang et al., 2011) is used in this study, where the TFN-based linguistic terms are used to address the ambiguity in human's judgments. By referring to Chang et al. (2011), steps regarding the fuzzy DANP for the weight's determination are summarized below (steps 2.1-2.6).

***Figure 2a-2c** here*

Step 2.1. Create the initial direct influence (IDI) matrix by utilizing the linguistic terms corresponding to the TFN (see **Table A2** in ***Appendix***).

Step 2.2. Normalize the TFN-based IDI matrix such that at least one column or row, but not all, sums to one.

Step 2.3. Obtain the TFN-based total relation (TR) matrix while clarifying the interrelationships using the operational laws in DEMATEL (see **Table A3** in ***Appendix***).

Step 2.4. Form the TFN-based unweighted supermatrix according to the *TR* matrix.

Step 2.5. Calculate the TFN-based weighted supermatrix.

Step 2.6. Generate the TFN-based limited supermatrix and determine the fuzzy weights of the attributes, which are then transformed into the weighting result, $W = \left[w_1, w_2, \cdots, w_n \right]$, by using the defuzzification (see Eq. 1).

2.3 Description of the fuzzy FUCOM

A comprehensive assessment needs both the quantitative and qualitative attributes, where the data regarding the qualitative attributes can only be evaluated based on subjective judgments. Therefore, previous studies usually used the pair-wise comparison methods like AHP and best-worst method (BWM) to quantify the qualitative performances, by preserving the consistency in subjective statements. However, these methods are too complex to make comparisons when multiple alternatives are involved in. For addressing this issue, Pamučar et al. (2018) introduced a novel pair-wise comparison method, known as FUCOM, to reduce the number of comparisons from $m(m\text{-}1)/2$ (in AHP) or $2m\text{-}3$ (in BWM) to $m\text{-}1$ (where m refers to the number of alternatives for comparison). However, the FUCOM only allows the users to use crisp numbers to create comparisons, failing to address the epistemic uncertainty in subjective judgments. Therefore, this study combines the FUCOM with the TFN-based linguistic terms for quantifying the qualitative attributes under uncertainty. Based on the literature (Guo and Zhao, 2017; Pamučar et al., 2018), steps of the fuzzy FUCOM are offered below (steps 3.1-3.3).

Step 3.1. Rank the qualitative performances of the alternatives, i.e. starting from the alternative that performs the best in an investigated attribute to the alternative of the worst performance, as shown in Eq. 2.

$$A_{j(1)} > A_{j(2)} > \cdots > A_{j(m)} \tag{2}$$

Suppose there are m alternatives in Eq. 2, and “=” instead of “>” should be used when two adjacent alternatives have equal priority.

Step 3.2. Implement the fuzzy pair-wise comparisons, where the relative priority between the adjacent alternatives is made by using the TFN-based linguistic terms (see **Table A4** in ***Appendix***). For instance, if the comparative priority between the first alternative ($A_{j(1)}$) and the second one ($A_{j(2)}$) is “very high priority”, the corresponding pair-wise comparison is $\tilde{\varphi}_{1/2} = (2, 5/2, 3)$. Similarly, the complete comparisons regarding *m* alternatives are given in Eq. 3.

$$\left[\tilde{\varphi}_{1/2}, \tilde{\varphi}_{2/3}, \cdots, \tilde{\varphi}_{i/(i+1)}, \cdots, \tilde{\varphi}_{(m-1)/m}\right] \tag{3}$$

Step 3.3. Determine the optimal fuzzy priorities. According to the value of $\tilde{\varphi}_{i/(i+1)}$, the optimal fuzzy priorities ($\tilde{p}$) regarding the corresponding adjacent alternatives can be denoted as $\tilde{p}_i / \tilde{p}_{(i+1)} = \tilde{\varphi}_{i/(i+1)}$. Similarly, based on the mathematical transitivity of the comparative priorities ($\tilde{\varphi}_{i/(i+2)} = \tilde{\varphi}_{i/(i+1)} \otimes \tilde{\varphi}_{(i+1)/(i+2)}$), it has $\tilde{p}_i / \tilde{p}_{(i+2)} = \tilde{\varphi}_{i/(i+1)} \otimes \tilde{\varphi}_{(i+1)/(i+2)}$ (Pamučar et al., 2018). To satisfy these conditions for all *i*, it requires to find a solution where the maximum absolute gaps $\left|\tilde{p}_i / \tilde{p}_{(i+1)} - \tilde{\varphi}_{i/(i+1)}\right|$ and $\left|\tilde{p}_i / \tilde{p}_{(i+2)} - \tilde{\varphi}_{i/(i+1)} \otimes \tilde{\varphi}_{(i+1)/(i+2)}\right|$ for all *i* are minimized. Considering the presence of TFN, the TFN-based constrained optimization model (see Eq. 4) is created to determine the fuzzy priority $\left[\tilde{p}_1^*, \tilde{p}_2^*, \cdots, \tilde{p}_m^*\right]$ by referring to (Guo and Zhao, 2017; Pamučar et al., 2018).

$$\begin{aligned} &\min \max_i \left\{ \left|\tilde{p}_i / \tilde{p}_{(i+1)} - \tilde{\varphi}_{i/(i+1)}\right|, \ \left|\tilde{p}_i / \tilde{p}_{(i+2)} - \tilde{\varphi}_{i/(i+1)} \otimes \tilde{\varphi}_{(i+1)/(i+2)}\right| \right\} \\ &s.t. \begin{cases} \sum_{i=1}^{m} DF(\tilde{p}_i) = 1 \\ 0 \le p_i^l \le p_i^m \le p_i^u \\ i = 1, 2, \cdots, m \end{cases} \end{aligned} \tag{4}$$

where $\tilde{p}_i = (p_i^l, p_i^m, p_i^u)$ and $\tilde{\varphi}_{i/(i+1)} = \left(\varphi_{i/(i+1)}^l, \varphi_{i/(i+1)}^m, \varphi_{i/(i+1)}^u\right)$ are TFNs, while *DF* refers to the defuzzification (see Eq. 1).

After introducing a TFN-based objective of $\tilde{\delta} = (\delta^l, \delta^m, \delta^u)$, Eq. 4 is transformed into a nonlinearly constrained optimization problem, as given in Eq. 5. Since $\delta^l \le \delta^m \le \delta^u$, if there is a crisp value *k* satisfies $k \le \delta^l$, then Eq. 6 can be obtained by transforming Eq. 5.

$$
\min \tilde{\delta}
$$
$$
\text{s.t.}\begin{cases}
\left|\tilde{p}_i / \tilde{p}_{(i+1)} - \tilde{\varphi}_{i/(i+1)}\right| \le \tilde{\delta},\ \forall i \\
\left|\tilde{p}_i / \tilde{p}_{(i+2)} - \tilde{\varphi}_{i/(i+1)} \otimes \tilde{\varphi}_{(i+1)/(i+2)}\right| \le \tilde{\delta},\ \forall i \\
\sum_{i=1}^{m} DF\left(\tilde{p}_i\right) = 1 \\
0 \le p_i^l \le p_i^m \le p_i^u,\ i = 1, 2, \cdots, m
\end{cases} \tag{5}
$$

$$
\min k
$$
$$
\text{s.t.}\begin{cases}
\left|\dfrac{\left(p_i^l, p_i^m, p_i^u\right)}{\left(p_{i+1}^l, p_{i+1}^m, p_{i+1}^u\right)} - \left(\varphi_{i/(i+1)}^l, \varphi_{i/(i+1)}^m, \varphi_{i/(i+1)}^u\right)\right| \le k,\ \forall i \\
\left|\dfrac{\left(p_i^l, p_i^m, p_i^u\right)}{\left(p_{i+2}^l, p_{i+2}^m, p_{i+2}^u\right)} - \left(\varphi_{i/(i+1)}^l \times \varphi_{(i+1)/(i+2)}^l, \varphi_{i/(i+1)}^m \times \varphi_{(i+1)/(i+2)}^m, \varphi_{i/(i+1)}^u \times \varphi_{(i+1)/(i+2)}^u\right)\right| \le k,\ \forall i \\
\sum_{i=1}^{m} DF\left(\tilde{p}_i\right) = 1 \\
0 \le p_i^l \le p_i^m \le p_i^u,\ i = 1, 2, \cdots, m
\end{cases} \tag{6}
$$

By solving Eq. (6), the optimal fuzzy priorities are offered, which should be then defuzzied by running Eq. 1 to represent the quantified performances of the alternatives.

2.3 Description of the interval VATOPSIS

Table 1 shows that several MADM methods like TOPSIS, DEA, GRA, and PROMETHEE can be used to rank the desalination alternatives. Among which, the TOPSIS proposed by Hwang and Yoon (1981) usually works satisfactorily by resorting to a compromise ranking logic, i.e. the best option should simultaneously have the shortest distance from the ideal solution and the farthest distance from the nadir solution. Moreover, the TOPSIS method could fully use the attribute information, and does not require attribute preferences to be independent, making itself suitable for the decision-making issues with multiple, even interrelated attributes (Behzadian et al., 2012). However, the traditional TOPSIS ranks the alternatives only according to the absolute scores associated with the attribute performances, failing to address the relative balance regarding the multi-attributes. As illustrated in **Figure 3**, such limitation can be understood by using a simple example with two alternatives (A_1 and A_2) and two attributes (C_1 and C_2), and the ideal and nadir performances are respectively (1, 1) and

(0.1, 0.1). It's hard to tell the difference between A_1 and A_2 since they have similar compromise distances by using the TOPSIS, even though the value of TOPSIS(A_1) is slightly higher than that of TOPSIS(A_2). However, considering the importance of balance in the sustainability issues, A_2 would be more preferable than A_1.

Recently, some works (Moradi-Aliabadi and Huang, 2016; Xu et al., 2017; 2018b) incorporated the relative balance among multi-attributes into the sustainability assessment, by recognizing that a real sustainable option should not only have a satisfactory performance rating but also a balanced direction toward the ideal solution. Accordingly, this study proposes a novel vector-aided TOPSIS (VATOPSIS) method for the prioritization of RE-powered desalination systems, which not only fully uses the attributes information by considering both the ideal and nadir solutions (as the TOPSIS does), but also incorporates both the absolute performance and relative balance among the attributes by resorting to the vector function. Here, **Figure 4** shows the principle of the VATOPSIS method. In reality, the data of attribute is usually available in a certain range rather than a crisp value (Wang et al., 2019); therefore, this study incorporates the interval number into the VATOPSIS to support the real-world decision-making process, via the following four steps (step 4.1-4.5).

***Figure 3** here*

***Figure 4** here*

Step 4.1. Build the standardization decision-making (*DM*) matrix. Supposing there are *m* alternatives and *n* attributes, the interval data of the attributes should be normalized by using Eq. 7.

$$\left[r_{ij}^L, r_{ij}^U\right] = \left[\frac{f_{ij}^L}{\sqrt{\sum_{i=1}^{m}\left[\left(f_{ij}^L\right)^2 + \left(f_{ij}^U\right)^2\right]}}, \frac{f_{ij}^U}{\sqrt{\sum_{i=1}^{m}\left[\left(f_{ij}^L\right)^2 + \left(f_{ij}^U\right)^2\right]}}\right] \quad (7)$$

where $\left[f_{ij}^L, f_{ij}^U\right]$ is the initial collected data of the *i*-th alternative regarding the *j*-th attribute (represented by interval number), while $\left[r_{ij}^L, r_{ij}^U\right]$ is the corresponding normalized version. Notably, the data regarding the qualitative attribute (quantified by the fuzzy FUCOM) is also denoted as $\left[f_{ij}^{L}, f_{ij}^{U} \right]$, and $f_{ij}^{L} = f_{ij}^{U}$. Subsequently, the fuzzy DANP-determined weight is combined with the normalized performance for establishing the standardization *DM* matrix as given in Eq. 8.

$$DM = \begin{bmatrix} w_1\left[r_{11}^L, r_{11}^U\right] & w_2\left[r_{12}^L, r_{12}^U\right] & \cdots & w_N\left[r_{1n}^L, r_{1n}^U\right] \\ w_1\left[r_{21}^L, r_{21}^U\right] & w_2\left[r_{22}^L, r_{22}^U\right] & \cdots & w_N\left[r_{2n}^L, r_{2n}^U\right] \\ \vdots & \vdots & \ddots & \vdots \\ w_1\left[r_{m1}^L, r_{m1}^U\right] & w_2\left[r_{m2}^L, r_{m2}^U\right] & \cdots & w_N\left[r_{mn}^L, r_{mn}^U\right] \end{bmatrix} = \begin{bmatrix} \left[z_{11}^L, z_{11}^U\right] & \left[z_{12}^L, z_{12}^U\right] & \cdots & \left[z_{1n}^L, z_{1n}^U\right] \\ \left[z_{21}^L, z_{21}^U\right] & \left[z_{22}^L, z_{22}^U\right] & \cdots & \left[z_{2n}^L, z_{2n}^U\right] \\ \vdots & \vdots & \ddots & \vdots \\ \left[z_{m1}^L, z_{m1}^U\right] & \left[z_{m2}^L, z_{m2}^U\right] & \cdots & \left[z_{mn}^L, z_{mn}^U\right] \end{bmatrix} \quad (8)$$

Step 4.2. Determine the ideal and nadir reference options. Based on the feature of TOPSIS, the ideal reference (A^+) option and the nadir one (A^-) are given in Eq. 9.

$$\begin{cases} A^+ = \left\{ z_1^+, z_2^+, \cdots, z_N^+ \right\} = \left\{ \left(\max_i z_{ij}^U \mid j \in BE \right), \left(\min_i z_{ij}^L \mid j \in CO \right) \right\} \\ A^- = \left\{ z_1^-, z_2^-, \cdots, z_N^- \right\} = \left\{ \left(\min_i z_{ij}^L \mid j \in BE \right), \left(\max_i z_{ij}^U \mid j \in CO \right) \right\} \end{cases} \quad (9)$$

where *BE* stands for a benefit attribute with a higher value indicating a better performance (like market share), while *CO* refers to a cost attribute where a lower value of the attribute is desirable (like water production cost).

Step 4.3. Obtain the separation measures by using the vector's projection. In this step, the Euclidean distances in TOPSIS are replaced by the vector's projections for analyzing the relative performance of each alternative compared with the ideal/nadir options. To be specific, the similarity between an investigated alternative (A_i) and the ideal (or the nadir) option can be obtained by running Eq. 10.

$$\begin{cases} P_i^+ = \mathrm{Proj}\left(A_i, A^+\right) = \left\| A_i \right\| \cos\left(A_i, A^+\right) \\ P_i^- = \mathrm{Proj}\left(A_i, A^-\right) = \left\| A_i \right\| \cos\left(A_i, A^-\right) \end{cases} \quad (10)$$

where $\left\| A_i \right\| = \left[\sqrt{\sum_{j=1}^{n} \left(z_{ij}^L \right)^2}, \sqrt{\sum_{j=1}^{n} \left(z_{ij}^U \right)^2} \right]$ is the norm of the vector function of the *i*-th alternative, representing its absolute performance rating; while

$$\cos\left(A_i, A^*\right) = \left[\frac{A_i \cdot A^+}{\left\| A_i \right\| \left\| A^+ \right\|} \right] = \left[\frac{\sum_{j=1}^{n} (z_{ij}^L z_j^*)}{\sqrt{\sum_{j=1}^{n} \left(z_{ij}^L \right)^2} \times \sqrt{\sum_{j=1}^{n} \left(z_j^+ \right)^2}}, \frac{\sum_{j=1}^{n} (z_{ij}^U z_j^*)}{\sqrt{\sum_{j=1}^{n} \left(z_{ij}^U \right)^2} \times \sqrt{\sum_{j=1}^{n} \left(z_j^+ \right)^2}} \right]$$ and

$$\cos\left(A_i, A^-\right) = \left[\frac{A_i \cdot A^-}{\|A_i\|\|A^-\|}\right] = \left[\frac{\sum_{j=1}^{n}(z_{ij}^L z_j^-)}{\sqrt{\sum_{j=1}^{n}\left(z_{ij}^L\right)^2} \times \sqrt{\sum_{j=1}^{n}\left(z_j^-\right)^2}}, \frac{\sum_{j=1}^{n}(z_{ij}^U z_j^-)}{\sqrt{\sum_{j=1}^{n}\left(z_{ij}^U\right)^2} \times \sqrt{\sum_{j=1}^{n}\left(z_j^-\right)^2}}\right]$$ are respectively the cosine angles between the *i*-th alternative and the ideal/nadir options, implying the relative balance. Therefore, the value of P_i^+ (or P_i^-) is still presented by interval number, and $P_i^+ = \left[\left(P_i^+\right)^L, \left(P_i^+\right)^U\right]$(or $P_i^- = \left[\left(P_i^-\right)^L, \left(P_i^-\right)^U\right]$)

Step 4.4. Compare the alternatives by introducing a combined coefficient. The similarities between the pairs of $A_i \sim A^+$ and $A_i \sim A^-$ should be normalized by using Eq. 11 for better comparison.

$$\begin{cases} NP_i^+ = \dfrac{P_i^+}{\|A^+\|} = \left[\left(NP_i^+\right)^L, \left(NP_i^+\right)^U\right] = \left[\dfrac{\left(P_i^+\right)^L}{\|A^+\|}, \dfrac{\left(P_i^+\right)^U}{\|A^+\|}\right] \\ NP_i^- = \dfrac{P_i^-}{\|A^-\|} = \left[\left(NP_i^-\right)^L, \left(NP_i^-\right)^U\right] = \left[\dfrac{\left(P_i^-\right)^L}{\|A^-\|}, \dfrac{\left(P_i^-\right)^U}{\|A^-\|}\right] \end{cases} \tag{11}$$

In Eq .11, the value of NP_i^+ (or NP_i^-) ranges from 0 to1, while a value being close to 1 represents a high similarity, and vice versa. Therefore, Eq. 12 determines the deviations between the performances of the pair of $A_i \sim A^+$ and $A_i \sim A^-$, respectively.

$$\begin{cases} DP_i^+ = \left|1 - NP_i^+\right| = \left[\left(DP_i^+\right)^L, \left(DP_i^+\right)^U\right] = \left[1 - \left(NP_i^+\right)^U, 1 - \left(NP_i^+\right)^L\right] \\ DP_i^- = \left|1 - NP_i^-\right| = \left[\left(DP_i^-\right)^L, \left(DP_i^-\right)^U\right] = \left[1 - \left(NP_i^-\right)^U, 1 - \left(NP_i^-\right)^L\right] \end{cases} \tag{12}$$

Since a real sustainable option should be similar to the ideal option while being different from the nadir one, a combined coefficient (*CC*) in Eq 13 is used to rank the alternatives in a compromise way, and a lower value of *CC* implies a better option. Noting that the value of *CC* ranges from 0 to 1, where *CC*=0 if $DP_i^+ = 0$, representing that the positive ideal solution can be found if the investigated alternative is the same as the ideal option; on the contrary, where *CC*=1 if $DP_i^- = 0$, implying that the investigated alternative has the same performance of the nadir option.

$$CC_i=\frac{DP_i^+}{DP_i^+ + DP_i^-}=\left[CC_i^L, CC_i^U\right]=\left[\frac{\left(DP_i^+\right)^L}{\left(DP_i^+\right)^U+\left(DP_i^-\right)^U},\frac{\left(DP_i^+\right)^U}{\left(DP_i^+\right)^L+\left(DP_i^-\right)^L}\right] \tag{13}$$

Step 4.5. Rank the alternatives by using a possibility measure. Since the value of *CC* in Eq. 13 is still in the form of the interval number, falling to indicate the best option. Therefore, this study used a well-practiced possibility measure (Xu and Da, 2002) for the final ranking, i.e. the *CC* values of any two alternatives (*i* and *j*) can be compared by running the formula of $T_{ij}=\max\left\{1-\max\left(\frac{CC_j^U-CC_i^L}{CC_j^U-CC_j^L+CC_i^U-CC_i^L},0\right),0\right\}$, and T_{ij}>0.5 implies that $CC_i>CC_j$. Subsequently, a possibility matrix (*PM*) involving all the pair-wise comparisons (regarding *m* alternatives) is created (see Eq. 14); based-on which, the final score (*FS*) of each RE-powered desalination system can be determined after aggregating the values in each row in *PM* (see Eq. 14), and a lower *FS* signifies a better option.

$$PM=\begin{vmatrix} T_{11} & T_{12} & \cdots & T_{1m} \\ T_{21} & T_{22} & \cdots & T_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ T_{m1} & T_{m2} & \cdots & T_{mm} \end{vmatrix} \Rightarrow FS=\begin{vmatrix} \left(\sum_{j=1}^{m} T_{1j}+0.5m\text{-}1\right)\Big/ m(m-1) \\ \left(\sum_{j=1}^{m} T_{2j}+0.5m\text{-}1\right)\Big/ m(m-1) \\ \vdots \\ \left(\sum_{j=1}^{m} T_{mj}+0.5m\text{-}1\right)\Big/ m(m-1) \end{vmatrix} \tag{14}$$

In Eq. 14, the diagonal elements (T_{ii}) of the matrix are all 0.5, and $T_{ji}=1-T_{ij}$.

2.4 Establishment of the sustainability assessment framework

Figure 5 offers an overview of the mathematical framework for the sustainability assessment of RE-powered desalination systems. In which, system definition (**Stage 1**) should be conducted on a case-by-case basis, where the alternative systems and the evaluation attributes are selected according to the actual conditions of the investigated cases and the subjective preferences of the stakeholders/decision-makers. **Stage 2** uses the fuzzy DANP (steps 2.1-2.6) to assign the weights to the interrelated attributes. **Stage 3**, utilizes the fuzzy FUCOM (steps 3.1-3.3) to quantify the performance regarding the qualitative attributes, meanwhile, it collects the data of the quantitative attributes from related literature. Based on the collected data and the determined weights, **Stage 4** ranks the alternative systems by using the interval VATOPSIS method (steps 4.1-4.5).

***Figure 5** here*

3. Case Study

An illustrative case regarding six RE-powered desalination systems is studied to demonstrate the feasibility of the framework. Notably, each alternative system refers to its typical configuration without the consideration of specific equipment models, and thus provides an overall picture regarding the combination of renewable energy sources and desalination units with a macroscopic viewpoint. Therefore, assessment data for the quantitative criteria in the case study were collected from scattered literature resources; meanwhile, three experts, i.e. one senior engineer from a RO-desalination plant, two professors whose expertise are respectively the desalination technologies and the renewable energy systems, were asked to contribute their insightful judgments regarding the determination of the weights (by using both fuzzy DANP and fuzzy AHP), and scoring of the qualitative attributes (by using FUCOM).

***Figure 6a-6f** here*

3.1 Stage 1-System definition in the case study

The system definition embraces two actions, i.e. determining the alternative systems and selecting the evaluation attributes. Notably, the users can add new alternatives (attributes) or delete the original ones according to the actual conditions of the investigated cases.

3.1.1 Step 1.1-Determine the alternative systems in the case study

By referring to the literature (Abdelkareem et al., 2018; Al-Karaghouli and Kazmerski, 2013), six RE-powered desalination systems (see **Figure 6a-6f**) are considered in the case study and described below.

A_1. Solar thermal-powered multistage flash (ST-MSF). **Figure 6(a)** shows the schematic of a typical ST-MSF configuration, which comprises an array of solar collectors, storage tanks, a power conversion system, and an MSF unit. Solar collectors can convert solar radiation into thermal energy, and transfers this heat to a fluid (usually water or oil). The collected thermal energy is thus carried away from the circulating fluid to the thermal storage tanks, from which is recalled for use when solar radiation is insufficient. The thermal energy from the storage system is exploited by a power conversion system consisting of a pre-heater, an evaporator, and a superheater, resulting in plenty of steams for driving the desalination unit. The MSF unit is a multi-stage thermal desalination process. In which, pre-heated feedwater pass through a series of closed tanks (stages) set at progressively lower pressures, undergoing sudden evaporation that known as flashing; some feedwater rapidly flashes and forms vapors, then the vapors condense on the surface of preheating tubes, simultaneously producing freshwater and transferring heat to the following feedwater inside the tubes in the next stage (Alsehli et al., 2017).

A_2. Solar thermal-powered multi-effect distillation (ST-MED). **Figure 6(b)** depicts an ST-MED configuration. Compared to the ST-MSF system, the ST-MED also relies on the solar collectors to collect solar energy during the sunny day, while requiring the thermal storage and the power conversion system for the energy supply and conversion, respectively. As for the unit of MED, it is also a thermal process by using multiple separation stages or “effects”. In the first effect, the feedwater is heated by external heat in tubes, and some feedwater evaporates, and this vapor transfers into the tubes of the next effect, heating and evaporating more water. Each effect can reuse the energy from the previous effect, lowing temperatures and pressures after each one (Chaibi and El-Nashar, 2009).

A_3. Geothermal-powered multi-effect distillation (GEO-MED). As shown in **Figure 6(c)**, this system relies on the geothermal energy to power the thermal desalination of MED. The geothermal energy, in this case, refers to the low-enthalpy geothermal aquifers, which can be accessed at depths close to the surface down to the subsurface with a typical temperature of 50-90°C. For utilizing the geothermal energy, the high-temperature geothermal aquifers are extracted from the underground and then transferred to the surface under pressure via the production well; subsequently, the heat in the geothermal aquifers can heat the feedwater in the MED unit by using heat exchangers, and thus freshwater can be produced by matching the heating medium and the feedwater (Christ et al., 2017).

A_4. Wind energy-powered reverse osmosis (WE-RO). **Figure 6(d)** offers the schematic of a typical WE-RO configuration, which consists of a wind generator, a battery bank, an inverter, and a RO desalination unit. In which, wind turbines convert the kinetic energy of the wind into mechanical power and subsequently in electrical power by driving a generator. Due to the high intermittence of the wind energy, the battery bank is needed to store the output power and as an energy supply, which helps to smooth or sustain system operation. Since RO usually employs alternating current (AC) for the operation, the inverter should be used to convert the direct current (DC) from the battery output to AC (Tzen, 2009). The RO desalination unit is a pressure-driven membrane separation process that consists of pre-treatment, RO modules, and post-treatment, where several RO modules can be combined in parallel or in series for expanding the capacity or improving the quality of the freshwater. When the pressure of the pre-treated feedwater is higher than the osmotic pressure, the feedwater is passed through a semipermeable membrane that allows water to pass through and prevents salt particles from passing (Monnot et al., 2018).

A_5. Solar photovoltaic-powered reverse osmosis (PV-RO). **Figure 6(e)** shows a PV-RO configuration. Compared to the WE-RO system, the PV-RO also includes the battery bank, the DC/AC inverter, and the RO-desalination unit, and their corresponding operating strategies are mentioned in WE-RO. However, photovoltaic panels (in the PV-RO) instead of wind turbines (in the WE-RO) are used to drive the system operation. To be specific, PV panels convert sunlight into DC by using semiconductor PV cells that display the photovoltaic effect. The PV cells form PV modules that generate DC, while the voltage and current of the power generation unit can be increased by connecting several cells in series or parallel (Abraham and Luthra, 2011).

A_6. Solar photovoltaic-powered electrodialysis (PV-ED). **Figure 6(f)** depicts the schematic of a typical PV-ED system. Compared to the PV-RO system, the PV-ED also requires the PV panel and battery bank for supporting the desalination unit of ED; however, since ED can utilize DC for the desalination, the equipment of invert can be eliminated (Abraham and Luthra, 2011). The desalination unit of ED is an electrochemical separation process, which uses the electrical potential to drive salt through ion-selective membranes. To be specific, positive salt ions in the feedwater pass through the cation-permeable membrane, while the negative salt ions travel towards the anion-permeable membrane, leaving the desalinated water behind.

3.1.2 Step 1.2-Select the evaluation attributes in the case study

After reviewing the published literature regarding the comparison among desalination alternatives (Ibrahim et al., 2018; Wang et al., 2019; Abdelkareem et al., 2018), this study considers ten critical attributes from environmental (D_1), economic (D_2), social (D_3), and technical (D_4) dimensions to perform the sustainability assessment (see **Table 2**).

***Table 2** here*

3.2 Stage 2-Weights determination of the attributes in the case study

The fuzzy DANP combines two techniques (i.e. DEMATEL and ANP) to assign the weights to the interrelated attributes.

3.2.1 Steps 2.1~2.3- Obtaining the network among the attributes by DEMATEL

***Table 3** here*

As shown in **Table 3, Step 2.1** determined the initial direct influence matrix of the case study, by collecting the linguistic-based judgments regarding the influential grade among the attributes. Subsequently, **Step 2.2** converted the linguistic-based matrix into its TFN-based version, which was then divided by the maximum value of the sum of each column or row for the normalization. Based on the normalized matrix, **Step 2.3** employed the equations in **Table A2** in ***Appendix*** to calculate the direct and indirect influences of each attribute, and the result was depicted in **Figure 7**.

In **Figure 7**, the top three values in the horizontal axis are corresponding to the attributes of water cost production (C_4), market share (C_5), and energy consumption (C_9), implying that these attributes can strongly influence and be influenced by other attributes. Meanwhile, according to the positive values in the vertical axis, C_2-water utilization efficiency, C_7- inherent safety, C_8-service flexibility, C_9-energy consumption, and C_{10}-reliability & robustness, were characterized into the cause group, signifying that these attributes affect the others to a greater impact than being affected by other attributes. On the contrary, the attributes with the negative value in the vertical axis belong to the effect group.

<u>Figure</u> *<u>7 here</u>*

3.2.2 Steps 2.4~2.6-Determining the weights by ANP based on the DEMATEL outcome

According to the DEMATEL-derived network, the computational procedures of the ANP was executed to generate the unweighted supermatrix (**Step 2.4**), the weighted supermatrix (**Step 2.5**), and limited supermatrix (**Step 2.6**), orderly. After using Eq. 1 to defuzzify the TFN-based limited supermatrix, the weights of the attributes (presented by crisp values) can be obtained as shown in **Figure 7**, which demonstrates that the economic attributes, i.e. water production cost (C_4) and market share (C_5), would be the top two critical elements for the overall sustainability of the RE-powered desalination systems.

3.3 Stage 3-Data collection of the alternatives in the case study

This stage separately collected the qualitative performance and quantitative data of the attributes.

3.3.1 Steps 3.1~3.3-Quantifying the alternatives' performances regarding each qualitative attribute

This case study includes three qualitative attributes, i.e. job creation (C_6), service flexibility (C_8), and reliability & robustness (C_{10}). Each alternative system in the case study comprises both power generation unit and desalination unit. For avoiding confusions in comparison, the fuzzy FUCOM was individually used to quantify the relative priorities of the four power generation alternatives (ST, GEO, WE, and PV), and that of the four desalination technologies (MSF, MED, RO, and ED). Taking the data quantification of C_{10} as an example, ***Step 3.1*** offered the ranking of the power generation alternatives regarding C_{10} (GEO>ST=PV>WE), and that of the desalination technologies (MSF=MED>RO=ED). ***Step 3.2*** determined the comparisons of the two rankings, i.e. $\left[\tilde{\varphi}_{\text{GEO/ST}}, \tilde{\varphi}_{\text{ST/PV}}, \tilde{\varphi}_{\text{PV/WE}}\right]$ =[M,E,M] (for power generation), and $\left[\tilde{\varphi}_{\text{MSF/MED}}, \tilde{\varphi}_{\text{MED/RO}}, \tilde{\varphi}_{\text{RO/ED}}\right]$=[E,F,E] (for desalination). Subsequently, ***Step 3.3*** built the corresponding optimization models as given in Eq. 15.

$$
\begin{array}{cc}
\text{(For power generation)} & \text{(For desalination technologies)} \\
\min\ k^1 & \min\ k^2 \\
s.t.\left\{\begin{array}{l}
\left|\frac{p^l_{GEO}}{p^u_{ST}}-1\right| \le k^1, \left|\frac{p^m_{GEO}}{p^m_{ST}}-\frac{3}{2}\right| \le k^1, \left|\frac{p^u_{GEO}}{p^l_{ST}}-2\right| \le k^1 \\
\left|\frac{p^l_{ST}}{p^u_{PV}}-1\right| \le k^1, \left|\frac{p^m_{ST}}{p^m_{PV}}-1\right| \le k^1, \left|\frac{p^u_{ST}}{p^l_{PV}}-1\right| \le k^1 \\
\left|\frac{p^l_{PV}}{p^u_{WE}}-1\right| \le k^1, \left|\frac{p^m_{PV}}{p^m_{WE}}-\frac{3}{2}\right| \le k^1, \left|\frac{p^u_{PV}}{p^l_{WE}}-2\right| \le k^1 \\
\left|\frac{p^l_{GEO}}{p^u_{PV}}-1\right| \le k^1, \left|\frac{p^m_{GEO}}{p^m_{PV}}-\frac{3}{2}\right| \le k^1, \left|\frac{p^u_{GEO}}{p^l_{PV}}-2\right| \le k^1 \\
\left|\frac{p^l_{ST}}{p^u_{WE}}-1\right| \le k^1, \left|\frac{p^m_{ST}}{p^m_{WE}}-\frac{3}{2}\right| \le k^1, \left|\frac{p^u_{ST}}{p^l_{WE}}-2\right| \le k^1 \\
\frac{1}{6}\sum_{\substack{x=\text{GEO,ST,}\\ \text{PV,WE}}} \left(p^l_x + 4p^m_x + p^u_x\right) = 1 \\
p^l_x \le p^m_x \le p^u_x, x = \text{GEO,ST,PV,WE} \\
p^l_x \ge 0, x = \text{GEO,ST,PV,WE}
\end{array}\right.
&
s.t.\left\{\begin{array}{l}
\left|\frac{p^l_{MSF}}{p^u_{MED}}-1\right| \le k^2, \left|\frac{p^m_{MSF}}{p^m_{MED}}-1\right| \le k^2, \left|\frac{p^u_{MSF}}{p^l_{MED}}-1\right| \le k^2 \\
\left|\frac{p^l_{MED}}{p^u_{RO}}-\frac{3}{2}\right| \le k^2, \left|\frac{p^l_{MED}}{p^u_{RO}}-2\right| \le k^2, \left|\frac{p^l_{MED}}{p^u_{RO}}-\frac{5}{2}\right| \le k^2 \\
\left|\frac{p^l_{RO}}{p^u_{ED}}-1\right| \le k^2, \left|\frac{p^m_{RO}}{p^m_{ED}}-1\right| \le k^2, \left|\frac{p^u_{RO}}{p^l_{ED}}-1\right| \le k^2 \\
\left|\frac{p^l_{MSF}}{p^u_{RO}}-\frac{3}{2}\right| \le k^2, \left|\frac{p^l_{MSF}}{p^u_{RO}}-2\right| \le k^2, \left|\frac{p^l_{MSF}}{p^u_{RO}}-\frac{5}{2}\right| \le k^2 \\
\left|\frac{p^l_{MED}}{p^u_{ED}}-\frac{3}{2}\right| \le k^2, \left|\frac{p^l_{MED}}{p^u_{ED}}-2\right| \le k^2, \left|\frac{p^l_{MED}}{p^u_{ED}}-\frac{5}{2}\right| \le k^2 \\
\frac{1}{6}\sum_{\substack{y=\text{MSF,MED,}\\ \text{RO,ED}}} \left(p^l_y + 4p^m_y + p^u_y\right) = 1 \\
p^l_y \le p^m_y \le p^u_y, y = \text{MSF,MED,RO,ED} \\
p^l_y \ge 0, y = \text{MSF,MED,RO,ED}
\end{array}\right.
\end{array}
\quad (15)
$$

The optimal solutions (in Eq. 15) were calculated by using the software Lingo 11.0, after defuzzification (Eq. 1), the priorities regarding the two units can be given as [P_{GEO}, P_{ST}, P_{PV}, P_{WE}]=[0.358, 0.238, 0.238, 0.166], and [P_{MSF}, P_{MED}, P_{RO}, P_{ED}]=[0.331, 0.331, 0.169, 0.169]. Therefore, the quantified performance of each alternative regarding C_{10} was obtained via the combination of the obtained priorities, that is, [$P_{ST\text{-}MSF}$, $P_{ST\text{-}MED}$, $P_{GEO\text{-}MED}$, $P_{WE\text{-}RO}$, $P_{PV\text{-}RO}$, $P_{PV\text{-}ED}$]=[0.238+0.331, 0.238+0.331, 0.358+0.331, 0.166+0.169, 0.238+0.169, 0.238+0.169]=[0.569, 0.569, 0.688, 0.335, 0.408, 0.408]. Similarly, the quantified data of the three qualitative attributes were obtained according to the corresponding subjective judgments (see **Table A5** in ***Appendix***), and the results were given in **Table 4**.

Table 4 here

3.3.2 Step 3.4-Collecting the alternatives' performances regarding each quantitative attribute

As summarized in **Table 4**, the quantitative performances of each alternative were collected or calculated from related literature; notably, the data of quantitative attributes were presented by interval numbers with the consideration of the data fluctuations.

3.4 Stage 4-Alternatives prioritization of the case study

This section used the interval VATOPSIS to rank the RE-powered desalination alternatives. In **Step 4.1**, both the collected quantitative and qualitative data (in **Table 4**) were normalized by using Eq. 7; then, the standardization decision-making matrix was offered in Eq. 16 (after running Eq. 8). Accordingly, **Step 4.2** determined the ideal reference (A^{+}) and the nadir reference (A^{-}), as shown in Eq. 17.

$$DM = \begin{bmatrix} [39.5,40.5] & [1.1,2.4] & [26.7,30.8] & [6.9,34.4] & [16.1,22.5] & [39.7,39.7] & [7.3,8.8] & [3.3,3.3] & [33.5,52.3] & [32.4,32.4] \\ [29.5,29.9] & [1.4,3.8] & [26.3,41.3] & [15.8,19.9] & [38.6,45.1] & [39.7,39.7] & [10.2,11.7] & [5.0,5.0] & [23.2,36.0] & [32.4,32.4] \\ [4.8,4.8] & [1.4,3.8] & [26.6,48.0] & [8.9,12.4] & [3.2,9.7] & [34.6,34.6] & [8.0,10.2] & [21.4,21.4] & [23.2,36.0] & [39.2,39.2] \\ [0.4,0.6] & [2.4,4.8] & [21.2,33.2] & [44.7,62.6] & [58.0,64.4] & [28.4,28.4] & [4.4,5.1] & [21.4,21.4] & [34.3,51.5] & [19.1,19.1] \\ [1.2,3.3] & [2.4,4.8] & [19.7,31.1] & [80.4,107.3] & [99.8,106.3] & [36.8,36.8] & [4.4,4.4] & [14.9,14.9] & [34.3,51.5] & [23.2,23.2] \\ [0.7,7.2] & [7.6,8.6] & [15.8,25.5] & [71.5,80.4] & [16.1,22.5] & [36.8,36.8] & [5.1,5.1] & [10.0,10.0] & [12.9,34.3] & [23.2,23.2] \end{bmatrix} \times 10^{-3}$$

(16)

$$\begin{cases} A^{+} = \{0.4,\ 8.6,\ 15.8,\ 6.9,\ 106.3,\ 39.7,\ 4.4,\ 21.4,\ 12.9,\ 39.2\} \times 10^{-3} \\ A^{-} = \{40.5,\ 1.1,\ 48.0,\ 107.3,\ 3.2,\ 28.4,\ 11.7,\ 3.3,\ 52.3,\ 19.1\} \times 10^{-3} \end{cases} \quad (17)$$

After running Eq. 10 in **Step 4.3**, the similarity between each alternative (A_i) and the ideal/nadir reference can be offered. In **Step 4.4**, the similarity regarding each alternative was normalized by running Eq. 11; which were then transformed into the deviations between the performances of the pair of A_i~A^{+} and A_i~A^{-} by using Eq. 12; based on which, the combined coefficient (*CC*) was calculated by using Eq. 13, and the results were summarized in **Table 5**.

<u>Table 5 here</u>

Step 4.5 applied the possibility measure (*PM*) (Xu and Da, 2002) to compare the values of *CC* (persented by interval numbers). For instance,

$$T_{12} = \max\left\{1 - \max\left(\frac{CC_2^U - CC_1^L}{CC_2^U - CC_2^L + CC_1^U - CC_1^L}, 0\right), 0\right\} = 0.746 \text{ , and } T_{21} = 1 - T_{12} = 0.254 \text{ .}$$

Subsequently, *PM* can be created while the final scores (*FS*) were obtained (see Eq. 18). Since a lower value in *FS* indicates a more sustainable performance regarding the corresponding alternative, the ranking result of the six RE-powered desalination systems is determined as ST-MED>PV-RO>WD-PV>GEO-MED>ST-MSF> PV-ED.

$$PM = \begin{array}{c} A_1 \\ A_2 \\ A_3 \\ A_4 \\ A_5 \\ A_6 \end{array} \begin{bmatrix} 0.500 & 0.746 & 0.623 & 0.579 & 0.695 & 0.315 \\ 0.254 & 0.500 & 0.317 & 0.438 & 0.503 & 0.043 \\ 0.377 & 0.683 & 0.500 & 0.523 & 0.638 & 0.135 \\ 0.421 & 0.562 & 0.477 & 0.500 & 0.555 & 0.308 \\ 0.305 & 0.497 & 0.362 & 0.445 & 0.500 & 0.141 \\ 0.685 & 0.957 & 0.865 & 0.692 & 0.859 & 0.500 \end{bmatrix} \Rightarrow \begin{cases} FS_1 = 0.181 \\ FS_2 = 0.135 \\ FS_3 = 0.162 \\ FS_4 = 0.161 \\ FS_5 = 0.142 \\ FS_6 = 0.219 \end{cases} \quad (18)$$

4. Results and discussion

4.1 Sensitivity analysis

The proposed framework is a weight-based model, where the weights are determined based on professional perception, which could be different when different experts are involved in. Therefore, for validating the robustness of the decision framework, the weights of the 10 attributes were adjusted for the sensitivity analysis by conducting 60 tests. To be specific, the purpose of the sensitivity analysis aims to test if the weight-change will affect the ranking result significantly, where each attribute takes 30%, 60%, and 90% less or more weight than the original weight. Notably, weight-change in one attribute should be reflected in remaining attributes weights by modifying them proportionally and ensuring that the sum of all weights is equal to one.

Figure 8 here

As observed in **Figure 8**, the alternatives of ST-MED and PV-ED remain the best choice and the worst one in most cases, respectively. Taking the ST-MED as an example, it has a 65% chance of ranking at the first place while only a 6.7% chance of falling out of top two, implying that the MED desalination unit powered by the solar thermal energy always performs satisfactorily. However, it is also noticed that the sequences of the alternatives are sensitive to the weight-change. This phenomenon is understandable, and could be explained as: the weights are used to determine the absolute scores and relative balance among the multi-attributes, and both of them are incorporated into the prioritization. Therefore, weights in the proposed framework would play a more important role for affecting final ranking than usual, while such influence could be further amplified under uncertain conditions. Accordingly, accurately assigning the weights to the attributes is a critical step for making a proper decision.

4.2 Weights comparison between the fuzzy AHP and fuzzy DANP

The developed framework adopts the fuzzy DANP to determine the weights, which is characterized by addressing the interrelationships among the attributes. In this part, the necessity for considering the interrelationships is examined by comparing the weights that determined using the fuzzy DANP with those determined using the fuzzy AHP. Notably, the same three experts were asked to make the pair-wise comparisons (see **Table A7** in ***Appendix***) for determining the fuzzy AHP-weights. For better comparison, the fuzzy AHP-weights were utilized to rank the six alternatives, which is then compared with the original ranking.

Figure 9a-9b *here*

As observed in **Figure 9a**, the two sets of weights are different. Taking the attribute of market share (C_5) as an example, the corresponding weight is 0.09 in fuzzy AHP, which is half of the value (0.18) that determined by fuzzy DANP. The reason for the difference originates from that only the direct effect of C_5 on the overall sustainability is considered, while the indirect effects generated from the interactions among the attributes are ignored. Besides, the ranking results determined by the two sets of weights are depicted in **Figure 9b**. In which, the geothermal powered multi-effect distillation (A_3) ranked as the most sustainable system by using the fuzzy AHP-weights. However, this result is unreasonable since the GEO-MED system is still in its infant stage, where the use of geothermal energy is constrained by the high cost of the power generation and the limited locations of geothermal activity (Abdelkareem et al., 2018). Therefore, ignoring the interrelationships among the attributes would lead to an irrational decision, which indirectly verifies the necessity of the utilization of fuzzy DANP.

4.3 Multi-Attributes Decision Making methods comparison

To verify the rationality and feasibility of the proposed interval VATOPSIS method, a comparison has been analyzed with two classical ranking approaches, i.e. TOPSIS and VIKOR. The selected two approaches, like the proposed method, can prioritize the alternative systems according to the proximity of each alternative to the ideal solution, offering a complete ranking result regarding the alternatives (Wu et al., 2020). For better comparison, the interval version of TOPSIS and VIKOR were used, by referring to Jahanshahloo et al. (2009) and Sayadi et al. (2009), respectively. In one-step forward, the similarity among the sequences determined by the three methods were quantitatively analyzed by using the Pearson correlation coefficient (Villacreses et al., 2017), where a higher value of the coefficient represents a higher similarity, and the value of 1 means a complete agreement.

***Figure 10** here*

According to the results in **Figure 10**, the following three conclusions could be offered. First, the sequences obtained by these methods are relatively like each other, for instance, the ST-MED always ranks at the first place, while the systems of ST-MSF and PV-ED are the most two unfavorable choices. Such similar rankings verified the feasibility of the proposed interval VATOPSIS method, which also confirmed the robustness of the ranking result regarding the best and the worst choices among the six alternatives. Second, there are differences in the three sets of rankings given the Pearson correlation coefficients of 0.94 for TOPSIS and VATOPSIS, and 0.83 for VIKOR and VATOPSIS, respectively. Therefore, the proposed VATOPSIS is more like TOPSIS than VIKOR. It is understandable since the TOPSIS provides with the VATOPSIS a fundamental ranking logic, i.e. a real sustainable option should simultaneously approach to the ideal solution while keeping away from the nadir solution. Third, the slight difference between VATOPSIS and TOPSIS could be attributed to the fact the relative balance among the multi-attribute is innovatively combined into the overall sustainability. More importantly, this innovation is consistent with the nature of sustainability to balance the performances from different dimensions, implying that the ranking derived from the VATOPSIS may be more rational than that from the TOPSIS.

5. Theoretical and Practical Implications

This work presents a hybrid MADM-based framework for the sustainability assessment of renewable energy-powered desalination systems. In the case study, renewable energy sources such as solar, wind, geothermal, and typical desalination processes like MSF, MED, RO, and ED have been investigated. The results of this work have important implications for both theory and practice.

For the theoretical contribution, (1). It creates a well-rounded assessment system embracing both quantitative and qualitative attributes from the environmental-economic-social-technical concerns; in which, the extended fuzzy FUCOM approach offers an easy, reliable, and humanistic way to collect the data of the qualitative attributes with the consideration of epistemic uncertainty. (2). It uses the fuzzy DANP to determine the weights, which provides a rational weighting result based-on the clarification of the causal-effect relationships among the multi-attributes. (3). It introduces the interval VATOPSIS to prioritize the RE-powered desalination systems under data uncertainties, via the combination of the interval numbers, vector algorithm, and the ranking logic of TOPSIS. The presented method can offer a reliable ranking result for the sustainability assessment by addressing the limitation of traditional ranking methods in respect of ignoring the relative balance among the multi-attributes under aleatory uncertainty.

In practice, a case study regarding six RE-powered desalination alternatives was investigated, which offers the following three implications: (1). A list of ten attributes provides the decision-makers with a well-rounded definition regarding the sustainability of the RE-powered desalination alternatives, where specific concerns from environmental impacts, economic prosperity, social responsibility, and technical performance can be considered. (2). The interrelationships among the ten attributes were clarified by using the fuzzy DANP, signifying that the attributes of water cost production (C_4), market share (C_5), and energy consumption (C_9) would be the roots for enhancing the overall sustainability; meanwhile, the weighting result reveals that the attributes in the economic concerns are more important than the attributes from other dimensions, which is basically in line with the existing works (Georgiou et al., 2015; Ghassemi and Danesh, 2013; Wang et al., 2019). Therefore, lowering the production cost and expanding the market share would be effective ways to guide the RE-powered desalination systems to a bright future. (3). The ranking result from the best to the worst is ST-MED>PV-RO>WE-RO>ST-MED>ST-MSF>PV-ED, implying the desalination technologies of MED and RO would be more suitable than MSF and ED to be integrated with the renewable energy; meanwhile, harnessing the solar energy (by either solar thermal or photovoltaic) to power the promising desalination technologies might be the best solution under current conditions. Such findings can be indirectly verified by several works and statistics, for instance, among the existing 131 renewable energy-powered desalination plants, around 43% and 27% of them are correspondingly driven by PV and solar thermal (Abdelkareem et al., 2018); therefore, the connection of PV cells to RO process, and the combination of solar thermal with MED have been recommended as promising options for the sustainable desalination (Abdelkareem et al., 2018).

6. Conclusions and Future Directions

This study developed a novel MADM-based framework for the sustainability assessment of renewable energy-powered desalination systems under uncertainties. In the framework, the triangular fuzzy numbers and interval values were respectively used to capture the epistemic and aleatory uncertainty; while three MADM methods were utilized or introduced for offering more rational and reliable results under uncertainties, i.e. fuzzy DANP to determine the weights, fuzzy FUCOM to quantify the qualitative attributes, and interval VATOPSIS to rank the alternative systems. After implementing a case study regarding six RE-powered desalination alternatives, the solar thermal-powered MED was identified as the best option. Moreover, by conducting the sensitivity analysis, and comparing the used weighting/ranking methods with other exiting methods, the rationality and feasibility of the developed framework can be verified.

In summary, the contribution of this study is threefold. First, the suggested weighting method (fuzzy DANP) can generate a rational weighting result by clarifying the interrelationships among the multi-attributes with the consideration of epistemic uncertainty. Second, the extended scoring method (fuzzy FUCOM) offers an easy, rigorous, and humanistic way for quantifying the qualitative performances, where the consistency in the subjective statements and the associated uncertainties can be simultaneously addressed. Third, the introduced ranking method (interval VATOPSIS) provides a rational way for prioritizing alternative systems under data uncertain, where the absolute scores and relative balance among the performances regarding the multi-attributes can be integrated for the final ranking.

As a new research object, the sustainability assessment of RE-powered desalination systems is affected by numerous factors and faces considerable uncertainties. Accordingly, from the mathematical viewpoint, there are still some limitations that need to be improved in the future, including: for avoiding omissions while reducing redundancies, it is suggested to use a systematic tool like Delphi to identify key attributes among extensive attribute candidates; for reaching a reliable consensus, it is expected to invite multiple stakeholders with divergent interests and preferences to take part in the decision-making process, which requires the necessity to extend the mathematical framework into a situation with multi-actor participation. Moreover, since the case study only provides an overview of typical configurations of six RE-powered desalination systems, wider and deeper researches are needed to improve the usefulness of the proposed framework in real case applications. To be specific, for expanding the research scope, more alternative systems should be considered in the sustainability assessment, such as using an integration of renewable energies for powering the RO unit (Maleki, 2018); while for deepening the investigation, optimized processes instead of generic configurations should be used, where their modeled equipment and operating strategies in detail are required for conducting the sustainability assessment (Peng et al., 2018).

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Table 1. Related studies regarding the multi-attributes decision making (MCDM)-based assessment of desalination systems

Reference	Attributers					Renewable Energy	Uncertainty		Method Futures
	En	Ec	So	Te	Ot		Epistemic	Aleatory	
(Wang et al., 2019)	2	2	2	4		No	Yes	Yes	AHP+TOPSIS
(Rufuss et al., 2018)	1	3	1	2		Solar stills	No	Yes	AHP+DEA
(Ibrahim et al., 2018)	5	3	5	3		No	No	No	AHP+ SWING+UNESCO
(Chamblás and Pradenas, 2018)	1	2		5		No	No	No	AHP+ELECTRE+TOPSIS
(Vivekh et al., 2017)	2	2	1	6		No	No	No	TOPSIS+PROMETHEE
(Marini et al., 2017)	5	5	8	15	8	Wind, PV	No	No	AHP
(Eusebio et al., 2016)	1	1		3		No	No	Yes	AHP+GRA
(Georgiou et al., 2015)	4	3	4	6		Wind, PV, Hybrid	No	No	AHP+PROMETHEE
(Ghassemi and Danesh, 2013)	2	2		6		No	No	Yes	AHP+TOPSIS
(Liu et al., 2013)	2	3	2	3	3	Wind, PV, Nuclear	No	No	AHP
(Hajeeh, 2010)		1		6		No	No	Yes	AHP
(Afify, 2010)	1	2	1	1		No	No	No	Multi-attributes analysis
(Rújula and KhalidouDia, 2010)	1	2		2		Wind, PV	No	No	Multi-attributes analysis
(Hajeeh and Al-Othman, 2005)	1	1		7	1	No	No	No	AHP

Note: En, Ec, So, Te, and Ot respectively stand for the dimension of environmental, economic, social, technical, and other concerns.

Table 2. Overview of the selected attributes

Dimension	Criterion	Units	Brief description
(D_1) Environmental	C_1 (Climate change)	$kgCO_2$ /m^3H_2O	The indirect carbon dioxide emissions associated to the RE-desalination process (Ibrahim et al., 2018).
	C_2 (Water utilization efficiency)	%	The rate of produced water to the water consumed in the RE desalination system (Ibrahim et al., 2018; Wang et al., 2019).
	C_3 (Land occupation)	m^2land /m^3H_2O	The needed land area for building both the RE-power generation and desalination plants (Ibrahim et al., 2018).
(D_2) Economic	C_4 (Water production costs)	USD /m^3H_2O	The average unit cost in economic life time of the RE-desalination plant (Abdelkareem et al., 2018; Ibrahim et al., 2018).
	C_5 (Market share)	%	The potion of a market dominated by a certain RE-powered desalination process (Abdelkareem et al., 2018; Wang et al., 2019).
(D_3) Social	C_6 (Job creation)	SE	The employment benefits associated with both the RE-power generation and desalination plants (Ibrahim et al., 2018).
	C_7 (Inherent safety)	Scores	The inherent danger and hazard in both the energy and water generation plants (Ibrahim et al., 2018).
(D_4) Technical	C_8 (Service flexibility)	SE	The possibility of the capability to be adapted to new, different, or changing requirements (Abdelkareem et al., 2018; Wang et al., 2019).
	C_9 (Energy consumption)	kWh /m^3H_2O	The total energy used for supporting the RE-desalination process (Abdelkareem et al., 2018; Wang et al., 2019).
	C_{10} (Reliability & Robustness)	SE	The vulnerability of the desalination technology & the reliability of the RE source (Ibrahim et al., 2018; Wang et al., 2019).

Note: SE stands for the subjective evaluation; which implies that the corresponding attribute should be measured based-on experts' judgments rather than be collected as objective data.

Table 3. The linguistic-based initial direct-influenced matrix

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}
C_1	N	N	N	VL	VL	N	N	N	H	N
C_2	VL	N	N	VL	VL	N	N	N	H	N
C_3	VL	N	N	L	VL	N	N	N	VL	VL
C_4	N	N	VL	N	VH	L	N	N	VL	L
C_5	VL	N	L	H	N	H	N	VL	L	VL
C_6	N	N	L	L	L	N	VL	N	N	N

C_7	N	N	N	L	L	L	N	VL	N	H
C_8	L	N	H	VH	H	H	N	N	H	VL
C_9	VH	VL	L	VH	H	VL	N	VL	N	VL
C_{10}	N	N	N	H	H	VL	VL	H	L	N

Table 4. The collected data of the alternatives' performances regarding each attribute

	C_1 ($kgCO_2/m^3$)	C_2 (%)	C_3 (m^2Land/m^3)	C_4 (USD/m^3)	C_5 %	C_6 -	C_7 Score	C_8 -	C_9 kWh/m^3	C_{10} -
A_1	[10.92, 11.21] (Raluy et al., 2005)	[12, 25] (Wang et al., 2019)	[4.78, 5.50] [a]	[1.0, 5.0] (Ghaffour et al., 2015)	[5, 7] (Statista, 2015)	0.57 [c]	[10, 12] [b]	0.04 [c]	[3.9, 6.1] (Al-Karaghouli and Kazmerski, 2013)	0.57 [c]
A_2	[8.16, 8.26] (Raluy et al., 2005)	[15, 40] (Wang et al., 2019)	[4.71, 7.39] [a]	[2.3, 2.9] (Abdelkareem et al., 2018)	[12, 14] (Statista, 2015)	0.57 [c]	[14, 16] [b]	0.07 [c]	[2.7, 4.2] (Al-Karaghouli and Kazmerski, 2013)	0.57 [c]
A_3	[1.32, 1.32] (Noorollahi et al., 2017)	[15, 40] (Wang et al., 2019)	[4.76, 8.58] [a]	[1.3, 1.8] (Christ et al., 2017)	[1, 3] (Statista, 2015)	0.50 [c]	[11, 14] [b]	0.28 [c]	[2.7, 4.2] (Al-Karaghouli and Kazmerski, 2013)	0.69 [c]
A_4	[0.12, 0.17] (Raluy et al., 2005)	[25, 50] (Nayar et al., 2017)	[3.79, 5.93] [a]	[6.5, 9.1] (Abdelkareem et al., 2018)	[18, 20] (Statista, 2015)	0.41 [c]	[6, 7] [b]	0.28 [c]	[4.0, 6.0] (Al-Karaghouli and Kazmerski, 2013)	0.34 [c]
A_5	[0.35, 0.90] (Raluy et al., 2005)	[25, 50] (Nayar et al., 2017)	[3.53, 5.56] [a]	[11.7, 15.6] (Abdelkareem et al., 2018)	[31, 33] (Statista, 2015)	0.53 [c]	[6, 6] [b]	0.20 [c]	[4.0, 6.0] (Al-Karaghouli and Kazmerski, 2013)	0.41 [c]
A_6	[0.20, 2.00] (Fernandez-Gonzalez et al., 2015)	[80, 95] (Nayar et al., 2017)	[2.82, 4.56] [a]	[10.4, 11.7] (Abdelkareem et al., 2018)	[5, 7] (Statista, 2015)	0.53 [c]	[7, 7] [b]	0.13 [c]	[1.5, 4.0] (Al-Karaghouli and Kazmerski, 2013)	0.41 [c]

[a] the data are the aggregations of the land requirements of renewable energy production (Evans et al., 2009) and desalination technology (Sommariva, 2010).

[b] the data are calculated by using an index-based approach (Heikkilä, 1999), see **Table A6** in ***Appendix*** for detailed descriptions.

[c] the data are the quantified performances by using the fuzzy FUCOM.

Table 5. Parameters for the interval vector-aided technique for order of preference by similarity to ideal solution (VATOPSIS) technique

	P^*	P^-	NP^*	NP^-	DP^*	DP^-	CC
A_1	[0.04, 0.06]	[0.05, 0.08]	[0.36,0.45]	[0.37,0.59]	[0.55,0.64]	[0.41,0.63]	[0.43,0.67]
A_2	[0.06, 0.08]	[0.05, 0.07]	[0.50,0.61]	[0.38,0.47]	[0.39,0.50]	[0.53,0.62]	[0.35,0.54]
A_3	[0.04, 0.05]	[0.04, 0.05]	[0.29,0.38]	[0.28,0.39]	[0.62,0.71]	[0.61,0.72]	[0.44,0.57]
A_4	[0.07, 0.10]	[0.07, 0.09]	[0.56,0.78]	[0.47,0.64]	[0.22,0.44]	[0.36,0.53]	[0.23,0.75]
A_5	[0.11,0.14]	[0.10,0.13]	[0.87, 1.13]	[0.68, 0.91]	[0.13, 0.14]	[0.09, 0.32]	[0.29, 0.60]
A_6	[0.04,0.05]	[0.08,0.10]	[0.34,0.42]	[0.55,0.70]	[0.58,0.66]	[0.30,0.45]	[0.52,0.74]
A^+	0.12	0.03	1.00	0.23	0.00	0.77	0.00
A^-	0.04	0.14	0.29	1.00	0.71	0.00	1.00

Appendix

Table A1. Operational laws for triangular fuzzy numbers and interval numbers (Xu, 2015)

	Triangular fuzzy numbers	Interval numbers
	$\tilde{A}=\left(a^l,\ a^m,\ a^u\right),\tilde{B}=\left(b^l,\ b^m,\ b^u\right)$	$A=\left[a^L,a^U\right],\ B\left[b^L,b^U\right]$
Addition	$\tilde{A}+\tilde{B}=\left[a^l+b^l,\ a^m+b^m,\ a^u+b^u\right]$	$A+B=\left[a^L+b^L,\ a^U+b^U\right]$
Subtraction	$\tilde{A}-\tilde{B}=\left[a^l-b^u,\ a^m-b^m,\ a^u-b^l\right]$	$A-B=\left[a^L-b^U,\ a^U-b^L\right]$
Multiplication	$\tilde{A}\times\tilde{B}=\left[a^l\times b^l,\ a^m\times b^m,\ a^u\times b^u\right]$	$A\times B=\left[a^L\times b^L,\ a^U\times b^U\right]$
Division	$\tilde{A}\div\tilde{B}=\left[a^l\div b^u,\ a^m\div b^m,\ a^u\div b^l\right]$	$A\div B=\left[a^L\div b^U,\ a^U\div b^L\right]$
Reciprocal	$\tilde{A}^{-1}=\left[1/a^u,1/a^m,1/a^l\right]$	$A^{-1}=\left[1/a^U,1/a^L\right]$
Power	$\tilde{A}^{\lambda}=\left[\left(a^l\right)^{\lambda},\left(a^m\right)^{\lambda},\ \left(a^u\right)^{\lambda}\right]$	$A^{\lambda}=\left[\left(a^L\right)^{\lambda},\ \left(a^U\right)^{\lambda}\right]$

Table A2. Linguistic scales and the corresponding triangular fuzzy numbers in fuzzy DANP (Wu and Lee, 2007)

Linguistics scale	Abbreviation	Triangular fuzzy number
No influence	N	(0,0,0.25)
Very low influence	VL	(0,0.25,0.5)
Low influence	L	(0.25,0.5,0.75)
High influence	H	(0.5,0.75,1)
Very high influence	VH	(0.75,1,1)

Table A3. Formulas for clarifying of the causal-effect relationships in fuzzy DANP (Xu and Dong, 2019)

Formula	Specification
$\tilde{r}_i=\sum_{j=1}^{n}\tilde{t}_{ij}$	the total direct/indirect influences of the *i*th attribute on the other factors
$\tilde{s}_j=\sum_{i=1}^{n}\tilde{t}_{ij}$	the total direct/indirect influences that the *j*th attribute receives from the others
$\left(\tilde{r}_i+\tilde{s}_i\right)$	the influences summarizations that is offered and received by the *i*th attribute
$\left(\tilde{r}_i-\tilde{s}_i\right)$	determine the causal or effect type of the *i*th attribute, where a positive value refers to the cause group, while a negative one is the effect group

Note: $\tilde{t}_{ij}$ is the element in the cell (*i*,*j*) of the TFN-based total relation matrix (step 3 in fuzzy DANP).

Table A4. Linguistic scales and the corresponding triangular fuzzy numbers in fuzzy AHP and fuzzy FUCOM (Ren et al., 2016)

Linguistic scale	Abbreviation	Triangular fuzzy number
Equally priority	E	(1, 1, 1)
Weakly high priority	W	(2/3, 1, 3/2)
Moderate high priority	M	(1, 3/2, 2)
Fairly high priority	F	(3/2, 2, 5/2)
Very high priority	V	(2, 5/2, 3)
Absolutely high priority	A	(5/2, 3, 7/2)
Reciprocals	RW, RM, RF, RV, RA	reciprocals of above

Table A5. The subjective judgments regarding the qualitative performances

Attribute	Ranking	Comparison vector
C_6	For power generation: *PV>ST=WE>GEO*	[*M, E, M*]
	For water production: *MSF=MED>RO=ED*	[*E, F, E*]
C_8	For Re-powered system: *WE-RO=GEO-MED >PV-RO>PV-ED>ST-MED>ST-MSF*	[*E, M, M, F, M*]
C_{10}	For power generation: *GEO>ST=PV>WE*	[*M, E, M*]
	For water production: *MSF=MED>RO=ED*	[*E, F, E*]

Table A6. Inherent safety analysis result for C_7

	Range	A1	A2	A3	A4	A5	A6
Process inherent safety indicator							
Inventory	0-5	1	5	2-3	2-3	2	2
Temperature	0-4	3-4	2-3	2-3	0	0	0
Pressure	0-4	1-2	2-3	1-2	3	3	3
Safety of equipment							
Inside battery limit area	0-4	1	1	1	1	1	1
Offsite battery limit area	0-3	3	3	3	0	0	0
Safe process structure	0-5	1	1	2	0	0	1
Total	25(max)	**10-12**	**14-16**	**11-14**	**6-7**	**6**	**7**

Table A7. The subjective judgments for determining the weights using fuzzy AHP

					D_1	C_1	C_2	C_3	D_2	C_4	C_5
	D_1	D_2	D_3	D_4	C_1	E	M	RW	C_4	E	V
D_1	E	RM	W	RM	C_2	RM	E	RF	C_5	RV	E
D_2	M	E	F	E	C_3	W	F	E			
D_3	RW	RF	E	RF				D_4	C_8	C_9	C_{10}
D_4	M	E	F	E	D_3	C_6	C_7	C_8	E	RM	RW
					C_6	E	F	C_9	M	E	W
					C_7	RF	E	C_{10}	W	RW	E

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