Criteria interdependency in Multi-criteria Decision-making on sustainability:

Desalination for resource recovery case study

By

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Abstract

There is a rising concern on the sustainability of Zero Liquid Discharge (ZLD) desalination. In this study, Multi-criteria Decision-making (MCDM) is applied to compare the sustainability performance of various ZLD scenarios, which is part of a Strong Sustainability (SS) assessment of desalination. ZLD desalination systems are considered to be complex and have intricate interdependence among various factors, which were seldom recognized in previous research. The purpose of this study is to explore the impact of interdependence among criteria on the MCDM process, with a desalination case study from Water Mining project used for demonstration. A transparent MCDM methodology is proposed in this study, which consists of Best Worst Method – Decision Making Trial and Evaluation Laboratory (BWM-DEMATEL), hierarchical clustering, and Preference Ranking Organization Method for Enrichment Evaluations (PROMETHEE).

In the desalination case study, the use of hierarchical clustering allows for the identification and preservation of both majority and minority opinions, based on which, the same ranking of desalination scenarios is produced through PROMETHEE. Concerning the interdependence among criteria, the results reveal that it can help identify the crucial factors for improvement of sustainability performance of the alternatives. In addition, by considering it, the understanding of criteria is enhanced, which leads to more concentrated opinions of stakeholders in the desalination case. However, the findings indicate that the influence of incorporating the criteria independency on the final decisions is restricted in cases insensitive to weight variation.

The application of BWM-DEMATEL method is a complex and time-consuming activity. Considering the effectiveness and the cost of implementation, BWM-DEMATEL might be not as worthy of application in this case study. Inspired by this, it is meaningful to develop an approach to estimate the impact of the interdependence among criteria on the alternatives ranking in a certain decision problem in the future.

Keywords: Multi-criteria Decision-making (MCDM); Zero Liquid Discharge (ZLD); Desalination; Sustainability; Interdependency.

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It took eight months starting from November 2022 for me to finish my master thesis, which is for the attainment of my master's degree in environmental engineering. This work aimed to develop a methodology to address criteria interdependencies in Multi-criteria Decision-making on sustainability. Transitioning from the field of environmental treatment to sustainability and operations research, this undertaking presented a novel and exciting challenge for me. Ultimately, we successfully developed a weighting approach and applied it to the sustainability evaluation of desalination scenarios in the Water Mining project. The accomplishment of this work would not have been possible without the assistance and support of numerous individuals. Therefore, I would like to take this opportunity to express my gratitude to everyone who has supported and contributed to the completion of my master's thesis project.

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Contents

List of Abbreviations

AHP	= Analytic Hierarchy Process
ANP	= Analytic Network Process
BWM	= Best Worst Method
CAPAX	= Capital expenditure
DEMATEL	= Decision-Making Trial and Evaluation Laboratory
DM	= Decision Maker
ELECTRE	= Elimination and Choice Translating Reality
GRA	= Grey Relation Analysis
IRM	= Influential Relation Map
MCDM	= Multi-criteria Decision-making
OPEX	= operational expenditure
PROMETHEE	= Preference Ranking Organization Method for Enrichment Evaluations
RO	= Reverse Osmosis
S.D.	= Standard deviation
SS	= Strong Sustainability
SWM	= Simple weighting method
TOPSIS	= Technique for Order of Preference by Similarity to Ideal Solution
WS	= Weak Sustainability
ZLD	= Zero Liquid Discharge

1. Introduction

1.1 Background

Desalination is an innovative and widely used technology that has shown great potential in alleviating the global water scarcity crisis by recovering fresh water from seawater or brackish (Panagopoulos, 2020; Panagopoulos et al., 2019). However, the environmental impact of desalination by-products, especially brine, has raised serious concerns (Pramanik et al., 2017). To minimize this environmental impact, researchers have proposed the Zero Liquid Discharge (ZLD) approaches, which aim to completely eliminate liquid waste from the plant while producing high-quality freshwater (Panagopoulos et al., 2019). However, their widespread implementation has been constrained by a range of challenges, such as the high energy requirements and high running costs. As a result, the sustainability of these ZLD technologies raises concern and must be carefully evaluated in terms of their environmental impact, economic feasibility, and social acceptability.

It is increasingly recognized that integrating brine mining processes into ZLD is possible to improve its sustainability performance. Seawater has significant potential as a resource for meeting future energy system material needs due to the large volumes of materials it contains (Lundaev et al., 2022). The extraction of materials from desalination brine presents an opportunity to create an additional economic benefit while addressing environmental concerns and resource depletion (Lundaev et al., 2022). Given the high value of minerals, integrating technologies to maximize the recovery of valuable materials additionally to the purification of water with the minimum energy consumption has the potential to enhance the sustainability performance of the treatment chain.

In light of these concerns and improvements in ZLD desalination, it is essential to conduct a comprehensive sustainability assessment of these desalination systems to analyze their environmental, economic, and social performance and make informed decisions about the most sustainable desalination option for a given context.

1.2 Sustainability assessment for desalination

1.2.1 Sustainability concept

The concept of sustainable development, as posited by the U.S. National Academy of Sciences (National Research 1999), is composed of three components. The first component refers to the object of sustenance, the second component concerns developmental aspects, and the third component deals with the interplay between the first two components. These components correspond to the tripartite nature of sustainable development by emphasizing its environmental, economic, and social dimensions. In the debate about sustainable development, the key question is whether natural capital can be substituted by man-made capital, which results in two concepts: Weak Sustainability (WS) and Strong Sustainability (SS) (Neumayer 1999) (Figure 1). WS states that “human capital” can substitute “natural capital” (Ekins, Simon et al. 2003). On the contrary, SS assumes that 'human capital' and 'natural capital' are complementary, but non-substitutable (Dietz and Neumayer 2007). In this study, SS is implemented for evaluation since it is a stricter definition and more relevant to the goal of sustainable development.

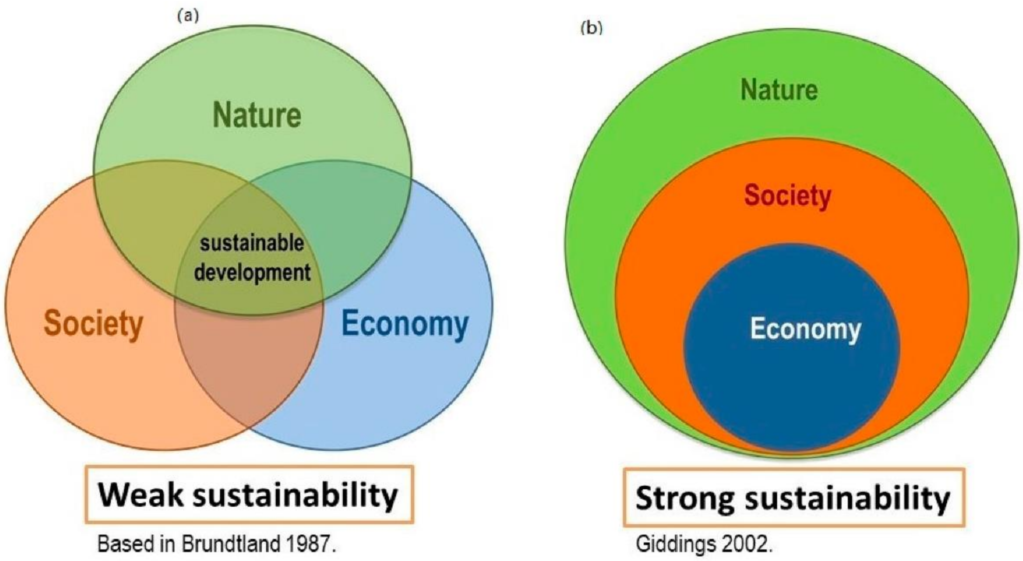


Figure 1. Graphic representations of weak and strong sustainability (Morandín-Ahuerma, Contreras-Hernández et al. 2019)

1.2.2 Sustainable desalination

Traditionally, sustainability assessment is based on the three dimensions of economic development, social development, and environmental protection (Saad, Nazzal et al. 2019). However, the multi-objective nature of ZLD desalination, which involves the maximal recovery of both water and minerals as well as the achievement of zero brine discharge, necessitates the inclusion of the technological dimension in the sustainability assessment process.

The technological dimension plays a critical role in handling the multi objectives of desalination. Appropriate selection of technologies, materials, and design approaches can optimize the recovery of freshwater and minerals while minimizing environmental impacts and costs. However, the multi-objective nature of desalination also poses higher demands on the technological aspect, resulting in a significant increase in system complexity. This complexity leads to greater interdependence and feedback among the technologies and between technology and other dimensions in the system, making it a challenging task to analyze the conflicting factors in sustainability assessment.

Overall, a sustainable desalination is defined in this study as a scenario with a comprehensive performance on SS, covering technological, economic, environmental, and social aspects.

1.2.3 Multi-criteria Decision-making (MCDM)

MCDM is applied as a part of sustainability assessment in this study. It is one of the mostly used tools to help decision-makers make choices when there are multiple criteria or objectives to consider (Siksnelyte, Zavadskas et al. 2018). MCDM involves a systematic process for structuring decision problems, identifying criteria, evaluating alternatives against those criteria, and synthesizing the results to make a decision. It is widely used in various fields, such as economics, environmental management, and public policy, where decisions need to be made based on conflicting objectives and preferences (Chung and Lee 2009, Baležentis, Baležentis et al. 2012, Ozkaya and Erdin 2020).

The general MCDM framework for sustainability assessment is presented in Figure 2. To rank the sustainability performances of alternatives, the MCDM process typically involves the following steps:

1) Identify the decision problem: Before making actual evaluation, a problem space needs to be defined. This includes determining the decision-making goal, the criteria required to measure the goal, and the alternatives to be ranked.

2) Weight determination: It aims at assigning relative weights to criteria to reflect their significance in the decision-making process. With the participation of stakeholders, the criteria are evaluated at the

individual level in this step, based on their interests, knowledge, and experience. Then different weight sets are generated from their judgements.

3) Group weighting: The different individual preferences (weight sets) are aggregated in this step. Usually a single weight set is produced through group discussion and averaging of opinions, so that consensus among stakeholders is achieved.

4) Alternatives ranking: The step of alternative ranking in MCDM involves comparing and ranking different alternatives based on their performance scores and the weights of criteria.

5) Sensitivity analysis: In this step, the sensitivity of the ranking to changes in the criteria or weights is evaluated. This analysis helps to identify the robustness of the decision.

6) Make the decision: Based on the ranking and sensitivity analysis results, the decision-maker makes the final decision.

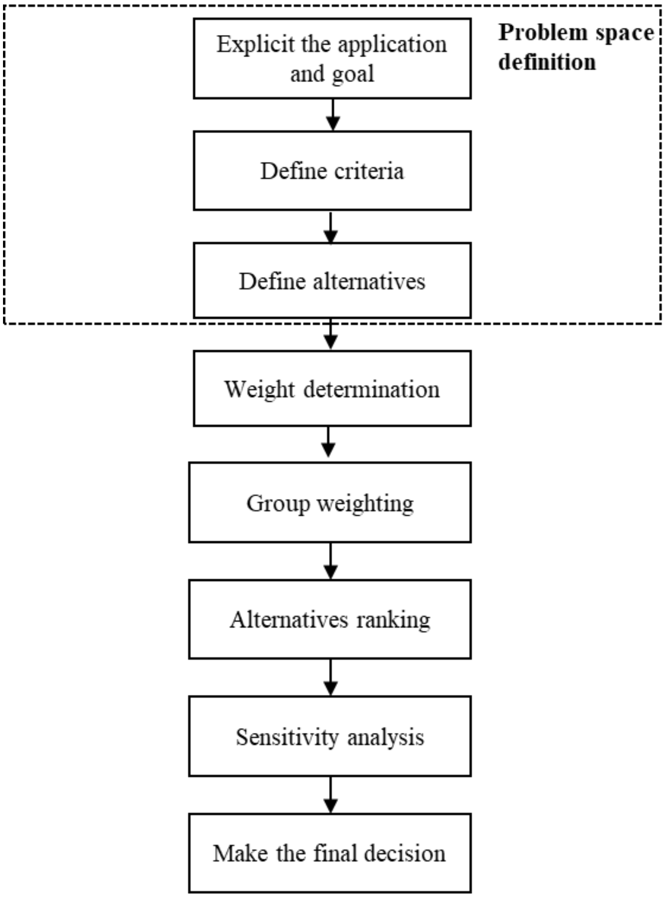


Figure 2. A common MCDM framework (adapted from Kumar, Sah et al. (2017))

MCDM is a flexible framework that can accommodate the use of various methods in each step to suit specific decision problems. This flexibility allows for different method combinations to be employed to effectively address the conflicts in stakeholders and sustainability factors. However, this also leads to some problems, such as the decrease in transparency.

1.3 Problem statement

As mentioned in previous sections, the development of ZLD technology has the potential to enhance its sustainability performance, but also brings new challenges to its sustainability assessment. MCDM is a good tool to guide decision-makers towards a sustainable desalination from a set of alternatives. It is used in this study to rank the sustainability performances of some ZLD desalination scenarios with multiple objectives, such as maximal water recovery, maximal resource recovery, and minimal energy consumption.

To design a purposeful and transparent MCDM methodology for the sustainability assessment of desalination, the key elements for the case study are identified and presented below. These elements were recognized as crucial factors that require careful consideration within the methodology design to ensure its effectiveness.

- Weight determination: Interdependence between criteria
- Group weighting: Information loss
- Alternatives ranking: Compensability in alternatives

Given the time limitation and current research, this study focuses on the design of weight determination, addressing the interdependence between criteria in the decision-making process. It is important to note that the aforementioned discussion provides only a concise overview of the research gaps, while a more comprehensive analysis is presented in Chapter 2.

1.4 Research question and objective

The research objective is to explore the impact of interdepedence among criteria on the MCDM process for sustainability assessment. Then the following research questions can be formulated with the purpose of reaching the research objective:

Main research question: What are the effects of the interdependence among criteria on the MCDM process for sustainability assessment?

Sub-research question 1: “How can interdependence among criteria be incorporated in the weights?”

Sub-research question 2: “What are the changes in the decision outcomes resulting from incorporating interdependence among criteria?”

Sub-research question 3: “What are the potential drawbacks and benefits of incorporating interdependence among criteria into the MCDM process for sustainability assessment?”

To answer the first sub-question, a weighting method has to be developed to integrate the interdependence among criteria into the weights. To answer the second sub-question, the effects of incorporating interdependence among criteria on the weights and final ranking should be analyzed. To answer the third sub-question, a discussion is required to identify the practical significance and potential limitations of incorporating interdependence among criteria in specific decision problems.

1.5 Research structure

This section provides a comprehensive elaboration on the content of the individual chapters comprising this thesis. In Chapter 1, the necessities and challenges for sustainability assessment of ZLD desalination are explained. Besides, the research objectives and questions are formulated. In Chapter 2, a literature review is presented. It provides a comprehensive summary of the relevant research progress in sustainability assessment with MCDM and its application in desalination. Based on these, the research gaps are identified and a MCDM methodology is designed for the case study in this research. In Chapter 3, the case study and the proposed methodology are described. The data collection process and research tools are also mentioned. In Chapter 4, the results of the implementation of the methodology on case study are presented. The results include the clusters of stakeholders’ opinions, the criteria weights, and the rankings of alternatives. Based on these, the research questions are discussed and answered. In Chapter 5, the limitations of this research, as well as that of the proposed methodology are summarized. Recommendations are given for potential improvements and future research. Chapter 6 is an overview and conclusion of this study. It begins with the research objectives and ends with the research outcomes and reflections on the effects of interdependency on the MCDM process.

2. Literature review

In this chapter, a literature review is presented to provide an overview of the past research on sustainability assessment and desalination with MCDM. Its objectives including providing a comprehensive summary of the relevant research progress, evaluating the MCDM methodology in previous research, and thereby identifying the knowledge gaps and research needs for this study. Then a MCDM methodology is designed given the context of decision problem in this study.

The literature review was conducted using a systematic review approach. A comprehensive search was performed using various databases such as Scopus, Google scholar, and Science Direct with relevant keywords such as “desalination”, “sustainability assessment”, “MCDM” and their variations. The included publications were, as far as possible, highly relevant and cited, and mainly published within ten years.

Section 2.1 summarizes the relevant research progress in the application of MCDM in sustainability assessment and evaluates the existing MCDM methodologies for desalination. Section 2.2 performs a MCDM methodology design given the context of decision problem in this study. Section 2.3 concludes the research gaps identified in the literature review and proposes the research objectives.

2.1 Previous research

2.1.1 MCDM as a sustainability assessment tool in previous studies

As presented in Introduction, MCDM provides a good structure for decision-making on sustainability. It is widely used for sustainability assessment of various projects such as energy, agriculture, and supply chain. For instance, MCDM was used to assess the cropping sustainability at country level considering economic and environmental constraints (Balezentis, Chen et al. 2020). It applied three MCDM methods to compare different crop mixes and to ensure the robustness of analysis. Another study applied MCDM to assess the sustainability of hydrogen technologies (Ren, Fedele et al. 2013), where fifteen criteria related to economic, environmental, technological, and social-political aspects were aggregated to rank the sustainability performance of four hydrogen technologies. Govindan, Khodaverdi et al. (2013) applied MCDM to evaluate the supplier performance and seek for the most sustainable supplier, where quantitative scores and qualitative judgements of criteria and alternatives were integrated and eventually converted into a sustainability ranking of suppliers. These applications have shown that MCDM is a useful approach for evaluating sustainability performance of projects and make decisions on selecting the most sustainable one from alternatives. The extensive use of MCDM in sustainability assessment is due to its ability to handle multiple criteria simultaneously. It provides effective solutions facing multiple criteria and constraints and allows ranking and comparison on alternatives. In addition, MCDM allows analysis on qualitative and quantitative information simultaneously.

However, some studies have pointed out that MCDM has limitations, such as the subjectivity of criteria weights, the difficulty in integrating qualitative and quantitative criteria. Many MCDM methods used for sustainability assessment such as Analytic Hierarchy Process (AHP) and Decision-Making Trial and Evaluation Laboratory (DEMATEL), need subjective judgements from experts to determine the criteria weights, which introduced a lot of subjective uncertainties, reducing the reliability of the results (Li, Ren et al. 2020). Also, qualitative criteria requires subjective judgements to score and multiple conversions to be aggregated with quantitative criteria, which might result in uncertainties and information loss (Xu and Zhang 2013).

2.1.2 MCDM methodology and its application in desalination

There are various methods developed in previous studies for each stage of MCDM methodology. In weight determination, methods utilizing experts' judgements are often used to calculate the weights of criteria. These methods include Simple weighting method (SWM) (Pazouki, Teshnizi et al. 2022), AHP (Saaty 1988) and Analytic Network Process (ANP) (Saaty and Vargas 2006), etc. In group weighting, a consensus of stakeholders is often reached through group discussion and averaging the individual weights (Garmendia and Gamboa 2012). In alternatives ranking, utility-based methods and outranking methods are two main categories. Utility-based methods such as AHP and Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) (Büyüközkan and Çifçi 2011), synthesize the weights and performance scores in a unique index to indicate the ranking of alternatives (Cinelli, Coles et al. 2014). Outranking methods such as Elimination and Choice Translating Reality (ELECTRE) (Yadav, Mangla et al. 2018) and Preference Ranking Organization Method for Enrichment Evaluations (PROMETHEE) (Brans, Vincke et al. 1986), rank the alternatives based on their outranking relations from pairwise comparisons (Munda 2008). It is important to note that the ranking method also has consequences for the so-called weak/strong sustainability debate (Munda 2008). This is resulted from the compensability of ranking methods, which refers to the possibility of compensating for low criterion scores with other very high criterion scores (Munda and Nardo 2005). Utility-based ranking methods show high compensation degree which results in a weak sustainability. Outranking methods, on the contrary, are often non-compensatory and lead to a strong sustainability for the decision-making process.

Different MCDM methods can be combined freely in a MCDM methodology to fulfill certain requirements in each stage. For example, In order to assess the sustainability of crop farming, Balezentis, Chen et al. (2020) used SWM to demonstrate various weighting orientations and applied different ranking methods (AHP and TOPSIS) to verify the consistency of results. In the selection process for the most sustainable energy supply configuration for desalination units, Georgiou, Mohammed et al. (2015) aimed for low compensation during decision-making and consequently chose PROMETHEE for ranking. For weight determination, AHP was selected to maintain a simple and consistent weighting process.

Application of MCDM in desalination is a relative new topic. It is applied in a limited number of desalination projects for sustainability evaluation. 17 studies which applied complete a MCDM methodology for sustainability assessment were collected and presented in Table 1. It can be found from the table that there is a lot of space for the development of MCDM in sustainability assessment of desalination. Only a limited number of MCDM methods were applied in desalination. AHP and SWM are mostly used for weight determination, mainly because of their simplicity for use and reputation. The situation is similar in alternatives ranking, the MCDM applications in desalination have been conservative and simple, mainly relying on well-established and reputable methods such as AHP, TOPSIS.

It can be indicated from Table 1 that uncertainty is a main challenge in the decision making process of desalination. Some desalination applications employed uncertainty managements to handle the uncertainties from quantitative data and subjective judgements. Wang, Wang et al. (2019) developed a methodology for uncertainty management in desalination projects by combining interval number theory with AHP and TOPSIS. By replacing crisp numbers with interval numbers, the hesitations and ambiguity existing in human's judgments could be addressed. Ibrahim, Arafat et al. (2018) combined Swing with AHP to reduce the pairwise comparisons within criteria and thereby reduce the subjective uncertainty from experts' judgements. Besides, fuzzy set theory was combined with various MCDM methods such as AHP, TOPSIS, and Grey Relation Analysis (GRA) to handle the uncertainties in data and ambiguity existing in judgements of experts (Hajeeh 2010, Ghassemi and Danesh 2013, Eusebio, Huelgas-Orbecido et al. 2016, Xu, Ren et al. 2020). It is evident that decision-makers take the uncertainty seriously and hope to improve the quality of decision-making towards a sustainable desalination by solving it.

In addition, another noteworthy point is that although the ranking methods determines the sustainability degree of the whole process, it has been taken lightly in the existing MCDM of desalination applications. Most of the collected research in Table 1 performed a weak sustainability using utility-based ranking methods as AHP and

TOPSIS. However, such weak sustainability was not explicated or desired in their decision-making objectives. A few research applied multiple ranking methods in their methodology (Georgiou, Mohammed et al. 2015, Vivekh, Sudhakar et al. 2017, Chamblás and Pradenas 2018). Chamblás and Pradenas (2018) used AHP, TOPSIS, and ELECTRE to examine the robustness and consistency of the results. However, the mixing of utility-based methods (AHP and TOPSIS) and outranking method (ELECTRE) resulted in an inconsistency in the sustainability. The sustainability of the former was weak, while the latter was strong. Thus, it was impossible to judge the sustainability degree of the whole decision-making process. These problems in desalination application indicate a lack of awareness of the characteristics and intrinsic of MCDM methods, especially some characteristics that are very important to sustainability evaluation.

Overall, it can be concluded that there is a lack of transparency in the MCDM methodology of desalination applications. The transparency means that each element in the MCDM methodology related to the decision problem is well recognized and the reasons for the methodology design are explicit. However, nearly half of the collected studies did not specify how they designed the methodology part of MCDM. The remaining ones selected methods largely based on their ease of use and reputation, while only uncertainty management was highlighted in a few research. Therefore, the considerations for the MCDM methodology were limited and biased, and many factors such as sustainability degree were overlooked. However, these are not sufficient to support a clear and reliable decision-making process. The complexity of sustainability evaluation in desalination calls for more detailed and transparent MCDM methodology.

Therefore, to advance the field of sustainability evaluation in desalination, future research needs to focus on developing more purposeful and transparent MCDM methodologies. To ensure the transparency of the MCDM process, it is crucial to carefully consider and evaluate the selection of MCDM methods and criteria weights. This involves a systematic and comprehensive analysis of the key factors of the decision problem and the characteristics of MCDM methodology.

Table 1. MCDM application in desalination

	Weighting method	Reason for choice	Ranking method	Reason for choice	Sustainability degree	Uncertainty management	Reference
1	AHP	Simple and consistent	AHP, PROMETHEE	PROMETHEE avoids compensation; AHP is simple	Weak in AHP; Strong in PROMETHEE	-	(Georgiou, Mohammed et al. 2015)
2	AHP	Reputable	AHP	Reputable	Weak	-	(Lior and Kim 2018)
3	AHP		TOPSIS	To handle hybrid information	Weak	Interval number	(Wang, Wang et al. 2019)
4	AHP	-	TOPSIS	To handle the large number of criteria and alternatives	Weak	Fuzzy number	(Ghassemi and Danesh 2013)

5	AHP	To handle the large number of the criteria	AHP	-	Weak	-	(Marini, Palomba et al. 2017)
6	AHP	-	TOSIS, PROMETHEE	Reputable and easy to understand	Weak in TOPSIS; Strong in PROMETHEE	-	(Vivekh, Sudhakar et al. 2017)
7	AHP	-	AHP, TOPSIS, ELECTRE	To ensure a good and consistent result	Weak in AHP and TOPSIS; Strong in ELECTRE	-	(Chamblás and Pradenas 2018)
8	AHP	-	GRA	-	Weak	Fuzzy number	(Eusebio, Huelgas-Orbecido et al. 2016)
9	AHP	-	AHP	-	Weak	Fuzzy number	(Hajeeh 2010)

10	AHP	-	AHP	Mostly used	Weak	Swing	(Ibrahim, Arafat et al. 2018)
11	DEMATEL + ANP (DANP)	To overcome the problem of dependence and feedback among criteria and alternatives	TOPSIS	Able to provide a rigorous ranking sequence in the context of sustainability	Weak	Fuzzy number	(Xu, Ren et al. 2020)
12	SWM	-	UNESCO	-	Weak	-	(Aliewi, El-Sayed et al. 2017)
13	SWM	-	AHP	-	Weak	-	(Afgan, Darwish et al. 1999)
14	SWM	-	AHP	To handle hybrid information	Weak	-	(Afify 2010)

15	SWM	-	TOPSIS	Simple, and able to trade-off between a wide range of criteria	Weak	-	(Pazouki, Teshnizi et al. 2022)
16	SWM	-	TOPSIS	Simple and comprehensive	Weak	-	(Do Thi, Pasztor et al. 2021)
17	SWM	-	TOPSIS	Simple and comprehensive	Weak	-	(Alnajdi, Calautit et al. 2019)

2.2 MCDM methodology design

As highlighted in Section 2.1.2, establishing a transparent and purposeful design process for MCDM methodology necessitates identifying and prioritizing the specific requirements within the context of the case study. In this study, the decision-making goal is to perform a ranking of strong sustainability for ZLD desalination scenarios with multiple objectives. Given this specific context, the study identifies the important elements in each stage of MCDM methodology and specifies the requirements on them.

2.2.1 Weighting procedure design

Weighting involves determining the relative importance of each criterion in relation to the decision-making objective based on stakeholders' judgements. Various methods have been developed for weight determination, and the mostly used ones in sustainability assessment are presented in Table 2. SWM (Pazouki, Teshnizi et al. 2022) and Simo's procedure (Figueira and Roy 2002) have very straightforward and simple process to determine the weights, and they are widely applied because of this ease of use. However, they both lack of a good structure to help decision makers understand the decision problems. In SWM, decision makers assign certain values directly to criteria weight. While this method is suitable for simple decision problems with a limited number of criteria, it can be strongly influenced by the decision maker's preferences without an analytical structure. Simo's procedure has similar problems. It consists of associating a "playing card" with each criteria, the decision maker has to handle the cards in order to rank them, with inserting white cards between them to indicate the gap in their importance. Due to the limited availability of white cards to indicate the degree of importance, Simo's procedure easily leads to process criteria having the same importance in a not robust way and excluding certain subsets of weights (Figueira and Roy 2002).

Table 2. Weighting methods in MCDM for sustainability assessment

METHOD	ADVANTAGES	LIMITATIONS	USAGE FREQUENCY	MAIN APPLICATIONS
SWM	Simple and straightforward	Biased by DM's preference	Medium	Desalination; Bioenergy; Agriculture;

				Supply chain; Energy
Simo's procedure	Simple and reputable	Flawed logical structure	Low	Eco-management; Energy
AHP	Simple and easy to understand	• High risk of inconsistency • Criteria should be independent	high	Desalination; Tourism management; Water management; Energy
Best Worst Method (BWM)	• Simple and easy to understand • Little inconsistency	Criteria should be independent	Medium	Vendor selection; Water treatment; Energy; Agriculture
DEMATEL	Able to explore the influence among criteria	Large subjective uncertainty	Low	Energy
ANP / DANP	Able to overcome the problem of dependence and feedback among criteria	• Difficult for communication • Very high risk of inconsistency	Medium	Construction design; Supply chain; Vendor selection; Urban planning

AHP (Saaty 1988) and BWM (Rezaei 2015) are developed to provide a good interactive structure to guide decision makers through the decision problems, as well as to keep the simplicity. AHP allows a hierarchical structure for the decision problem, and guide decision makers to understand it through pairwise comparisons of elements starting from the bottom level. BWM takes one step further, it employs an optimization model for calculation, which can reduced the inconsistency resulted from the large number of pairwise comparisons. Therefore, they are very popular choices for current MCDM applications. However, most existing weighting methods in the literature, including AHP and BWM, assume the independence of criteria.

Factors in real-world decision problems are not independent. On the contrary, the interralationships between criteria and sustainability, as well as the interdependencies among criteria reflect the comprehensive dynamics of sustainability assessment. The interdependence refers to the extent to which criteria in a decision problem mutually influence one another, these influences can affect the relative importance of criteria. It can be found in Table 2 that DEMATEL (Si, You et al. 2018) and ANP/DANP (Saaty and Vargas 2006, Govindan, Kannan et al. 2015) are often used to overcome the interdependence among criteria in weight determination. Their commonality is to use a network structure to present the interactions in criteria. The weights are derived from an influence matrix, where each value represents the judgment of decision maker on the degree to which one criteria has on another. However, these methods are designed to be too complex procedurally. On the one hand, the conversion from influence matrix to the weights is a challenge for decision makers to understand. On the other hand, a large number of pairwise comparisons (much more than AHP) is required to indicate all the influences in the system. Such extensive judgements not only greatly increase the subjectivity of weight determination, but also make it difficult for the communication with stakeholders (Kadoić, Begičević Ređep et al.). A high demand on the knowledge and expertise of stakeholders is placed to understand and indicate the interdependences in criteria.

Overall, it is difficult for current weighting methods to satisfy simultaneously the ease of use and the resolution on the interdependence in criteria. In the case study of desalination, it is evident that the system is characterized by complexity and intricate interactions among various factors. For instance, energy consumption constitutes a significant expense in the desalination process, and higher energy usage typically results in increased operating costs. Additionally, high operation complexity of the system places a high requirment on the skills of technicians, which might reduce workforce hired locally. Therefore, the interaction of factors in this decision problem are strong. However, this has not received much attention in the current desalination studies, as most studies have mainly applied SWM and AHP methods, as described in Section 2.1.2.

Weighting methods considering the criteria interdependency should be applied to make well-informed decisions, despite their shortcoings. However, DEMATEL and ANP/DANP still exhibit limitations in effectively capturing the complex interrelationships between criteria. While they effectively present the interrelationships among criteria, they fail to incorporate some crucial aspects such as the direction of influence (positive or negative) and the direct influence of criteria on the decision-making goal. These missing elements limit the ability to fully capture the complex dynamics and impact of criteria on the overall decision-making process, and might greatly affect the decision outcomes. In light of these, a novel weight determination method namely BWM-DEMATEL is proposed to address some of the limitations, and a detailed description of the proposed method is given in Chapter 3.

2.2.2 Group weighting design

In group weighting, the different weight sets from various stakeholders in the previous step are aggregated. In this process, many existing studies aim to achieve consensus among stakeholders through averaging of opinions (Garmendia and Gamboa 2012). However, when dealing with a large number of stakeholders, conflicting opinions and extreme views may arise. Forcing consensus in such situations may result in a loss of valuable information and reduce the effectiveness of the decision-making process (Garmendia and Gamboa 2012). In addition, enforcing consensus may lead to disagreement and disengagement among stakeholders whose values are vastly different from the average (Proctor and Drechsler 2006).

It can be concluded from Section 2.1.2 that desalination poses a relatively novel and intricate challenge for decision-makers. This can lead to considerable discrepancies in their comprehension of this decision problem. Moreover, the inclusion of extra objective in desalination such as maximal resource recovery makes the problem even more difficult to analyze, giving rise to significant conflicts and divergence among stakeholders. Such diversity of opinions can greatly affect the ultimate decision, and is crucial for the analysis of interdependence between criteria in weight determination. As a result, consensus is not deemed necessary in this research to enable a more open and inclusive decision-making process. Instead, the application of hierarchical clustering is employed to avoid information loss and account for unpopular opinions in this study. In particular, hierarchical clustering is a widely used aggregation method and is applied to aggregate opinions from different stakeholders without necessarily forcing them to reach a consensus in MCDM process (Garmendia and Gamboa 2012). This method recognizes the potential divergence of opinions and permits the inclusion of even less prevalent viewpoints. By grouping together opinions that are similar, hierarchical clustering can provide decision-makers with insight into the distribution of opinions and facilitate informed decision-making. The specific description of hierarchical clustering employed in this study is given in Chapter 3.

2.2.3 Ranking procedure design

In alternatives ranking, the performance scores of alternatives and the weights of criteria are utilized to generate an overall ranking of the alternatives. Ranking methods have many characteristics related to the decision problem and perform differently across methods. The ranking procedure design requires making requirements for each characteristic regarding the case study context, so that the method which best meets the needs is selected.

Table 3 presents an overview of the important characteristics of MCDM ranking methods as outlined by Munda (2006), Cinelli, Coles et al. (2014). In-depth analyses and specific requirements for each characteristic are detailed (check Appendix A), and here a few selected characteristics along with further explanations are presented below. The selection of the ranking method employed in this study is based on a thorough examination of the existing literature and its adherence to these requirements.

Table 3. MCDM characteristic list

	Characteristic
Data situation	Uncertainty in criterion score
	Sensitivity to data difference
Feasibility concerning Use context	Simplicity
Calculation related	Type of problem solution

	Incommensurability
	Compensation degree and weight typology
	Comparability

- Uncertainty in criterion score

1) Description:

Uncertainty in criterion scores refers to the uncertain, imprecise, or missing information in calculating criterion scores. Many MCDM methods such as PROMETHEE and ELECTRE have the capability of handling uncertainty in criteria score. For those which do not have such ability, the usual approach is to integrate fuzzy set theory.

2) Requirement:

The MCDM method must be able to handle uncertain and imprecise information, as well as mixed quantitative and qualitative information.

3) Reason:

In the context of the sustainability assessment of the case study, the criteria of technological, environmental, and economic dimensions are mainly quantitative, while some criteria of the social dimension are qualitative. The quality of the evaluation depends on the availability of complete and accurate data. However, since the desalination project in Lampedusa is in the early stages, accurate and sufficient quantitative data is not always available, and imprecision in quantitative data needs to be handled during evaluation. In addition, qualitative information can lead to significant epistemic uncertainty, such as ambiguity in subjective judgments or lack of knowledge in parameterization, which also requires appropriate treatment (Xu, Ren et al. 2020). Overall, the ability to manage uncertainty is crucial during the MCDM process.

- Sensitivity in data difference

1) Description:

Sensitivity in data difference refers to the extent to which changes in the data used to evaluate the alternatives affect the ranking and selection of the best alternative in MCDM. Specifically, this sensitivity pertains to the degree of uncertainty in how much difference in one criterion score makes one alternative better than another. The common approach of adjusting the sensitivity in data difference is to introducing thresholds into MCDM methods.

2) Requirement:

It is important to incorporate preference and indifference threshold values in the MCDM decision-making model to handle data sensitivity.

3) Reason:

Data variation can significantly affect the final decision results, particularly when dealing with large uncertainties. For example, a 10k EUR difference in water production cost may be negligible in a full-scale desalination project, but could lead to opposite rankings in MCDM regarding economic criteria. To address this, it is necessary to account for the sensitivity in determining how much difference in one criterion makes one alternative better than another. This can be accomplished by introducing thresholds into the model, which can capture indifference and preference when comparing two alternatives.

- Compensation degree

1) Description:

Compensation degree is a key characteristic in MCDM, which refers to the possibility of compensating for low criterion scores with other very high criterion scores (Munda and Nardo 2005). It is closely related to the meaning of sustainability in the decision-making process and provide preference information among the sustainability criteria. In a full compensatory process, where only a weak sustainability concept is enforced, there is a complete substitutability in criteria. In contrast, in a partial or non-compensatory process, a strong sustainability concept is allowed. The choice on the compensation degree depends on the specific context and goals of the decision problem and should be carefully considered to ensure that the resulting evaluation is accurate and meaningful.

2) Requirement:

Partial or complete non-compensability is an essential requirement in the decision-making process for sustainability assessment.

3) Reason:

Non-compensatory multi-criteria methods are more suitable for sustainability assessments as they ensure that all important dimensions are considered, according to different stakeholder groups (Garmendia and Gamboa 2012). Compensation in decision-making refers to the ability of a good performance in one criterion to compensate for the poor performance in another criterion. For example, a high production efficiency can compensate for a large carbon dioxide emission to achieve a good overall performance. In this way weights are expressed as trade-offs, and the importance of criteria is diminished while the substitutability increases. However, high compensation may not indicate strong sustainability, especially when environmental and social aspects are damaged. Therefore, complete compensability is not recommended for sustainability assessments.

In light of the requirements for MCDM ranking methods, the chosen approach must possess a partially or non-compensatory nature to reinforce a strong degree of sustainability in the decision-making process. Moreover, it must have the capability to handle data uncertainty and the decision maker's preferences while simultaneously preserving incommensurability. Therefore, an outranking method that permits the application of thresholds is preferred. Given the simplicity of the method, PROMETHEE was selected over other outranking methods, such as ELECTRE, due to its lower number of required parameters. Furthermore, PROMETHEE can generate stable outcomes, which are of paramount importance since the decision-maker often cannot precisely determine the threshold values (Brans, Vincke et al. 1986). This feature enables the method to produce reliable results that can aid in the decision-making process. The specific description of PROMETHEE employed in this study is given in Chapter 3.

2.3 Research gaps in the literature review

The literature review indicates that there is a lack of transparency in the MCDM methodology design in sustainability assessment, which might lead to an incomplete perception of the decision problem. Specifically, there are three main gaps that have not been properly solved. It is important to note that these research gaps may not be limited in desalination.

- In the weight determination, the interdependence among criteria is not well addressed, including the missing of direct influence on the decision-making goal, and the direction of influence in criteria.

- In the group weighting, forcing consensus might result in an information loss (such as extreme opinions), which can reduce the quality of decision-making.

- In the alternatives ranking, the compensation between alternatives is seldom recognized, which is crucial for sustainability assessment and greatly affect the selection of ranking methods.

Given the time limitation and current research, this study focuses on the design of weight determination, whose key factor is the interdependence between criteria. For group weighting and ranking, hierarchical clustering and PROMETHEE are selected from literature to address the identified problems. A design roadmap is presented in Figure 3.

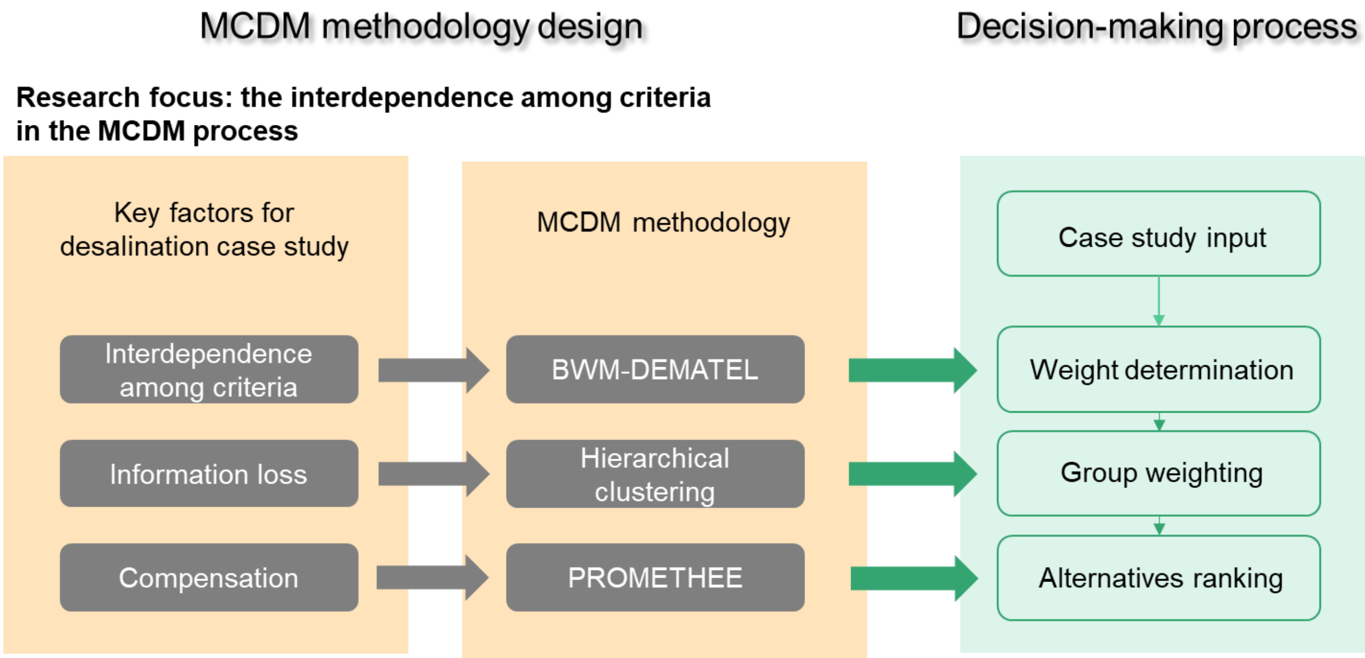


Figure 3. Design roadmap

3. Methodology

3.1 Case study description

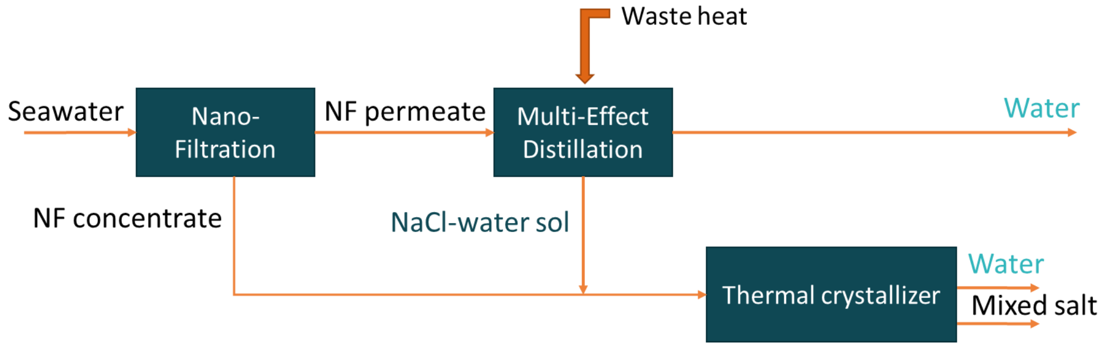
This section presents an overview of the case study in this research. It is about the evaluation and ranking of sustainability performance of desalination scenarios which are to be built in Lampedusa, Italy (from Water Mining Project, https://watermining.eu/). It is important to note that this study doesn't cover the construction of decision problem. The primary source of initial information for the case study is Water Mining Project, including the design of desalination scenarios, the establishment of sustainability criteria, and the determination of performance scores for these scenarios.

3.1.1 Background

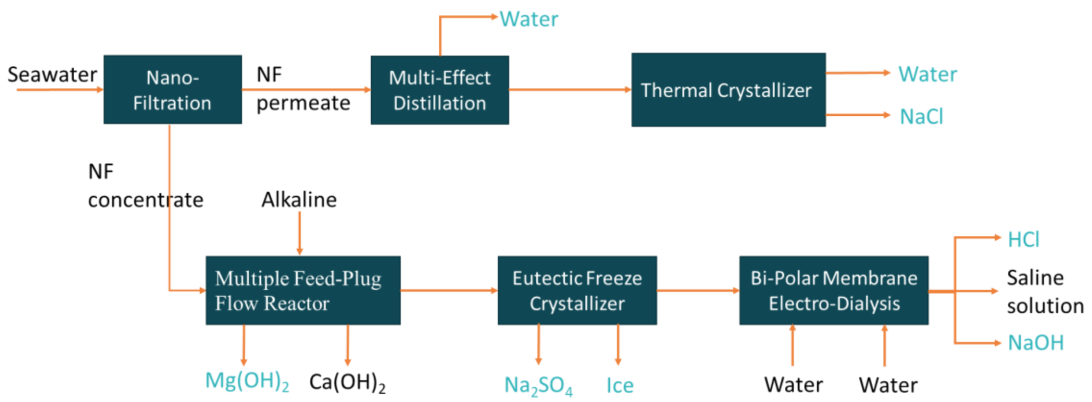
A novel desalination scenario aimed at maximizing water recovery, resource recovery and zero brine discharge simultaneously was proposed in Water Mining project. The process integrates several thermal-based and membrane technologies to produce high quality water with a circular economy approach, recovering high valuable minerals and employing energy from waste sources. It was installed at a pilot scale and tested as the power plant in the Sicilian Island of Lampedusa, Italy, where there is water and energy scarcity. To evaluate the feasibility of this advanced desalination process, its sustainability performance is to be evaluated and compared with other commonly used ZLD desalination scenarios through MCDM in this study.

3.1.2 Desalination scenarios

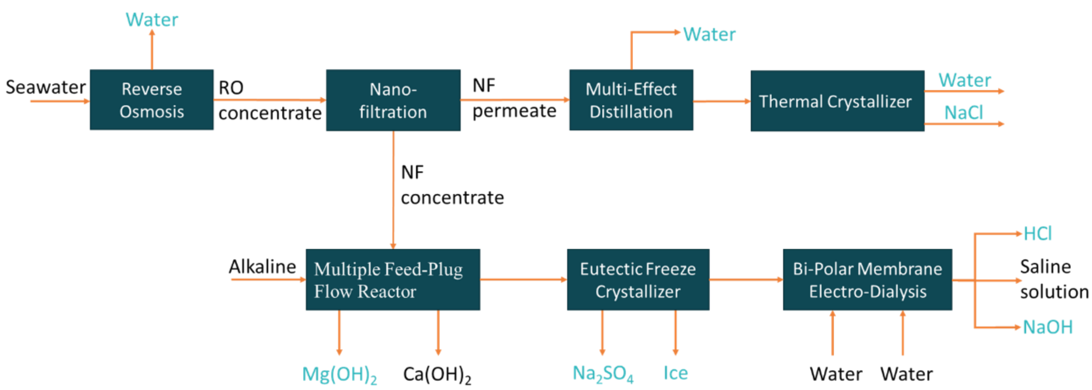
Four desalination scenarios are designed to be evaluated and ranked regarding their sustainability performances. Each scenario is designed with unique objectives in mind, and their treatment processes can be found in Figure 4. It is noteworthy that Scenario 2 was the one implemented and tested in Lampedusa.



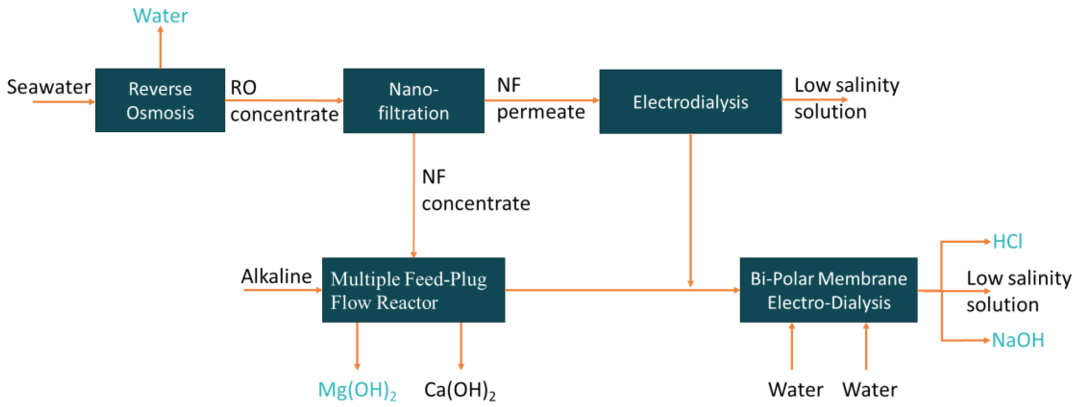
(a) Scenario 1: Water recovery.



(b) Scenario 2: Water mining case study.



(c) Scenario 3: Integrate RO plant with brine treatment.



(d) Scenario 4: Integrate RO plant with brine treatment.

Figure 4. Conceptual schemes of the four desalination scenarios

3.1.3 Desalination sustainability criteria

15 criteria are selected and classified into four dimensions: technological, economic, environmental, and social. The selected criteria are presented in Table 4.

Table 4. The selected desalination sustainability criteria

Dimension	Objective	Criteria	Unit
Technological	Improve Energy performance	Energy consumption	Mwh/year
	Increase water recovery	Quantity of water produced	m^3/year
	Increase efficiency	Resource efficiency	(%)
	Increase efficiency	Brine production	ton/year
Economic	Optimize Product value	Levelized cost	€/m^3

	Economic viability of the plant	CAPEX	€
		OPEX	€/year
	Profitability	Production efficiency	%
Environmental	Minimize Climate change impact	Carbon dioxide emission	(ton CO_2-Equ)
	Minimize Resource utilization	Water footprint	m^3/year
	Minimize human toxicity	Human toxicity	-
Social	Increase Social acceptance	Operational complexity	-
		Safe and healthy conditions	-
	Impact on employment created by local employers	Local employment	-
	Increase Social acceptance	Level of aesthetic acceptability	-

3.2 Mathematical description of MCDM methodology

In Section 2.2, a customized MCDM methodology is designed based on the specific requirements of the case study, and the elaborate mathematical formulations are comprehensively explicated within this section.

3.2.1 Weight determination: BWM-DEMATEL

The objective of weight determination is to derive the relative importance of each criterion by considering their interdependence, which is essential for evaluating desalination sustainability. The evaluation weight (Composite weight) of criteria can be decomposed into two components: the direct and indirect influence of each criterion on the decision-making goal. The weight of criteria can be mathematically expressed using Eq. (1). The direct influence of each criterion on the goal (Direct weight) can be calculated using common methods like AHP and BWM, which do not consider the interdependence among criteria. However, to quantify the indirect influence of each criterion on the goal, a method that integrates the interdependence among criteria into the weight of criteria is required.

$$\begin{aligned} &Evaluation\ weight \\ &= Direct\ influence\ of\ criteria\ on\ the\ goal \\ &+ indirect\ influence\ of\ criteria\ on\ the\ goal \end{aligned} \tag{1}$$

In order to determine the evaluation weight of the criteria, a novel approach that combines DEMATEL technique with BWM (BWM-DEMATEL) has been developed. The BWM method is used to calculate the direct weight, while the DEMATEL framework is employed for evaluating the interdependence among criteria and their integration.

DEMATEL is a useful tool for exploring the influence between different elements, and widely used in determination of interrelationships and criteria weights (Tseng 2011, Khalili-Damghani, Aminzadeh-Goharrizi et al. 2014, Quader and Ahmed 2016, Si, You et al. 2018). It is typically based on an influence matrix as shown in Eq. (2). The matrix indicates the direct influence that each factor has on another using an integer scale of "no influence," "low influence," "medium influence," "high influence," and "very high influence" for a factor set $F = \{F_1, F_2, \dots, F_n\}$. Then the individual direct-influence matrix $A = \left[a_{ij}\right]_{n\times n}$ can be formed, where all principal diagonal elements are equal to zero and a_{ij} represents the judgment of decision maker on the degree to which factor F_i affects F_j (Si, You et al. 2018).

$$\begin{array}{cccccc} & F_1 & \cdots & F_j & \cdots & F_n \\ F_1 & a_{11} & \cdots & a_{1j} & \cdots & a_{1n} \\ \vdots & \vdots & & \vdots & & \vdots \\ F_i & a_{i1} & \cdots & a_{ij} & \cdots & a_{in} \\ \vdots & \vdots & & \vdots & & \vdots \\ F_n & a_{n1} & \cdots & a_{nj} & \cdots & a_{nn} \end{array} \tag{2}$$

The proposed method adds the decision-making goal (G) as a new element to the influence matrix, with its values set to zero in the first row, as Saaty and Vargas (2006) recommended in ANP. The new influence matrix is shown in Eq. (3). Given criteria set $C = \{C_1, C_2, \dots, C_n\}$, the direct weights $w_d = [w_{id}]_{n\times1}$ are represented by the values in the first column, while the influences among criteria are represented by $\left[a_{ij}\right]_{n\times n}$.

$$\begin{array}{ccccccc} & G & C_1 & \cdots & C_j & \cdots & C_n \\ G & 0 & 0 & \cdots & 0 & \cdots & 0 \\ C_1 & w_{1\mathrm{d}} & a_{11} & \cdots & a_{1j} & \cdots & a_{1n} \\ \vdots & \vdots & \vdots & & \vdots & & \vdots \\ C_i & w_{id} & a_{i1} & \cdots & a_{ij} & \cdots & a_{in} \\ \vdots & \vdots & \vdots & & \vdots & & \vdots \\ C_n & w_{nd} & a_{n1} & \cdots & a_{nj} & \cdots & a_{nn} \end{array} \tag{3}$$

BWM developed by Rezaei (2015) is a decision-making analysis method designed to assist individuals in making complex decisions. It is founded upon the evaluation of the best and worst criteria and the subsequent determination of criterion weight through the comparison of each criterion's relative importance to the best and worst criteria. BWM is widely applied in various fields, such as determining the weights of evaluation criteria in site selection (Ecer 2021), waste treatment (Torkayesh, Malmir et al. 2021), energy (Lin, Lu et al. 2021), etc. Given its advantages in facilitating communication with stakeholders and minimal inconsistency, BWM is a suitable approach for calculating the direct weights.

The specific calculation steps of the proposed method (BWM-DEMATEL) are as follows:

Step 1: ***Calculate the direct influence of criteria on the goal using BWM.***

To derive the direct weights $w_d = [w_{id}]_{n\times1}$, the relative importance of each criterion to the goal is calculated using the Linear Best Worst Method (LBWM). This involves soliciting expert opinions on the best and worst criteria concerning the goal and using pairwise comparison to determine the preference of the best criterion over other criteria and the preference of other criteria over the worst criterion. A numerical scale ranging from 1 to 9 is utilized to express the degree of preference, with 1 indicating equal importance, and 9 indicating that one criterion is extremely more important than the other. The implementation of Linear BWM refers to Rezaei (2015), Rezaei (2016):

a) Determine the best (e.g. the most important), and the worst (e.g. the least important) criteria.

In this step, the decision-maker identifies the best and the worst criteria. No comparison is made at this stage.

Determine the preference of the best criterion over all the other criteria using a number between 1 and 9.

The resulting Best-to-Others (BO) vector would be $A_B = (a_{B1}, a_{B2}, \dots, a_{Bn})$, where a_{Bj} indicates the preference of the best criterion B over criterion j. It is clear that $a_{BB} = 1$.

b) Determine the preference of all the criteria over the worst criterion using a number between 1 and 9.

The resulting Others-to-Worst (OW) vector would be $A_w = (a_{1W}, a_{2W}, \dots, a_{nW})^T$, where a_{jW} indicates the preference of the criterion j over the worst criterion W. It is clear that $a_{WW} = 1$.

c) Find the direct weights $w_d = [w_{id}]_{n\times 1}$.

The direct weight is the one with minimum inconsistency, where $\frac{w_B}{w_j} = a_{Bj}$ and $\frac{w_j}{w_W} = a_{jW}$ can be satisfied. To satisfy these conditions for all j, the solution should minimize the maximum absolute differences $|w_B - a_{Bj}w_j|$ and $|w_j - a_{jW}w_W|$ for all j. A linear optimization model is applied as a solution to obtain the direct weights $w_d = [w_{id}]_{n\times 1}$:

$$\begin{aligned}
&\text{Min } \varepsilon \\
&s.t. \\
&|w_B - a_{Bj}w_j| \le \varepsilon, \quad \text{for all } j \\
&|w_j - a_{jW}w_w| \le \varepsilon, \quad \text{for all } j \\
&\textstyle\sum_J w_j = 1 \\
&w_j \ge 0 \qquad\qquad\quad \text{for all } j
\end{aligned} \tag{4}$$

Step 2: ***Calculate the influence among criteria using DEMATEL.***

This step is crucial for analyzing the complex relationships between different criteria. In this step, DEMATEL technique is used to explore the interdependence degree among criteria. It is used in literature to analyze the interdependent relationships among factors in a complex system (Si, You et al. 2018). The method can be summarized as follows (Hsu, Wang et al. 2012):

a) Obtain the direct-influence matrix. In this step, answers of respondents indicate the degree of direct influence each criteria i exerts on each criteria j. The influence degree is expressed by a_{ij}, using an integer scale ranging from 0 to 10 (going from "no influence (0)", to "very high influence (10)"). Then a direct-influence matrix $A = \left[a_{ij}\right]_{n\times n}$ is derived, within which all principal diagonal elements are equal to zero. The direct-influence matrix is presented as shown in Eq. (5).

$$A = \begin{bmatrix} a_{11} & \cdots & a_{1j} & \cdots & a_{1n} \\ \vdots & & \vdots & & \vdots \\ a_{i1} & \cdots & a_{ij} & \cdots & a_{in} \\ \vdots & & \vdots & & \vdots \\ a_{n1} & \cdots & a_{nj} & \cdots & a_{nn} \end{bmatrix} \tag{5}$$

Calculate the normalized direct-influence matrix. The normalized direct-influence matrix $X = \left[x_{ij}\right]_{n\times n}$ can be achieved by using Eq. (6) and Eq. (7):

$$X = A \times z \tag{6}$$

$$z = \min\left\{\frac{1}{\max\limits_{1\le i\le n} \sum_{j=1}^{n} a_{ij}}, \frac{1}{\max\limits_{1\le i\le n} \sum_{i=1}^{n} a_{ij}}\right\} \tag{7}$$

All elements in the matrix X are complying with $0 \le x_{ij} < 1$, and $0 \le \sum_i x_{ij} \le 1$ or $0 \le \sum_j x_{ij} \le 1$, and at least one column or one row of summation, but all, equals to one.

b) Derive the total-influence matrix T. A continuous decrease of the indirect effects of problems can be determined along the powers of X, e.g., $X^2, X^3, \ldots, X^h$ and $\lim\limits_{h\to\infty} X^h = [0]_{n\times n}$. The total-influence matrix $T = [t_{ij}]_{n\times n}$ is then computed by summing the direct effects and all of indirect effects by Eq. (8), in which I denotes the identity matrix.

$$T = X + X^2 + X^3 + \cdots + X^h = X(I - X)^{-1} \quad \text{when } h \to \infty \tag{8}$$

Explanation:

$$T = X + X^2 + X^3 + \cdots + X^h = X(I + X + X^2 + \cdots + X^{h-1})(I - X)(I - X)^{-1}$$
$$= X(I - X^h)(I - X)^{-1}$$

Then,

$$T = X(I - X)^{-1}, \qquad \text{when } h \rightarrow \infty$$

c) Produce the influential relation map (IRM). The summation of rows and columns from the total-influence matrix T are defined as vector R and S using Eq. (9) and Eq. (10):

$$R = [r_i]_{n\times 1} = \left[\sum_{j=1}^{n} t_{ij}\right]_{n\times 1} \tag{9}$$

$$S = [s_j]_{n\times 1} = \left[\sum_{i=1}^{n} t_{ij}\right]_{1\times n}^{T} \tag{10}$$

r_i is the i^{th} row sum in the matrix T and shows the sum of direct and indirect effects of criteria i on the other criteria. Similarly, s_j is thej^{th}column sum in the matrix T and shows the sum of direct and indirect effects that criteria j is receiving from the other criteria. When $i = j$, the horizontal axis vector $(R + S)$ named "Prominence" illustrates the strength of influences that are given and received of the criteria. It stands for the degree of central role that the criteria plays in the system. In addition, the vertical axis vector $(R - S)$ called " Relation" shows the net effect that the criteria contributes to the system. If $r_i - s_i$ is positive, then criteria i is influencing other criteria in the system and can be grouped into cause group; if $r_i - s_i$ is negative, then criteria i is being influenced by other criteria and should be grouped into effect group. Finally, an IRM can be created by mapping the dataset of $(R + S, R - S)$, which provides valuable insights for the interdependence of criteria in the system.

d) Calculate the influential weight of criteria. Utilizing the prominence $(R + S)$ obtained in previous steps, the weights of criteria can be calculated in DEMATEL. It is important to note that the weights calculated through this method represent the relative strength of influence of the criteria on the entire system, rather than the relative importance of criteria with respect to the goal of decision-making. The influence weight of criteria $w_I = [w_{iI}]_{n\times 1}$ is calculated through a normalization of prominence $(R + S)$ as follow:

$$w_{iI} = \frac{r_i + s_i}{\sum_{i=1}^{n} r_i + s_i} \ , i = 1, 2, \dots, n \tag{11}$$

Step 3: ***Integrating DEMATEL and BWM to determine composite weights.***

To obtain the composite weights, the direct weights $w_d = [w_{id}]_{n\times 1}$ from step 1 and the direct-influence matrix $A = \left[a_{ij}\right]_{n\times n}$ from step 2 are combined into a composite direct-influence matrix A_c , which is formed as Eq. (12):

$$A_c = \begin{array}{cccccccc} & G & C_1 & \cdots & C_j & \cdots & C_n \\ G & 0 & 0 & \cdots & 0 & \cdots & 0 \\ C_1 & w_{1\mathrm{d}} & a_{11} & \cdots & a_{1j} & \cdots & a_{1n} \\ \vdots & \vdots & \vdots & & \vdots & & \vdots \\ C_i & w_{id} & a_{i1} & \cdots & a_{ij} & \cdots & a_{in} \\ \vdots & \vdots & \vdots & & \vdots & & \vdots \\ C_n & w_{nd} & a_{n1} & \cdots & a_{nj} & \cdots & a_{nn} \end{array} \tag{12}$$

In accordance with the normalization approach outlined in step 2, the direct-influence matrix A_c is normalized to produce the normalized direct-influence matrix X_c using Eq. (13) and Eq. (14), where $d_j = \sum_{i=1}^{n} a_{ij}$.

$$X_C' = \begin{array}{cccccccc} & G & C_1 & \cdots & C_j & \cdots & C_n \\ G & 0 & 0 & \cdots & 0 & \cdots & 0 \\ C_1 & w_{1\mathrm{d}} & a_{11}/\mathrm{d}_1 & \cdots & a_{1j}/\mathrm{d}_j & \cdots & a_{1n}/\mathrm{d}_n \\ \vdots & \vdots & \vdots & & \vdots & & \vdots \\ C_i & w_{id} & a_{i1}/\mathrm{d}_1 & \cdots & a_{ij}/\mathrm{d}_j & \cdots & a_{in}/\mathrm{d}_n \\ \vdots & \vdots & \vdots & & \vdots & & \vdots \\ C_n & w_{nd} & a_{n1}/\mathrm{d}_1 & \cdots & a_{nj}/\mathrm{d}_j & \cdots & a_{nn}/\mathrm{d}_n \end{array} \tag{13}$$

$$X_c = X_C' \times \frac{1}{n+1} \tag{14}$$

The composite total-influence matrix T_c is then calculated using Eq. (8) and presented in Eq. (15), where the composite weights of criteria are represented by $w_c = [w_{ic}]_{n\times 1}$.

$$T_c = \begin{array}{c} \\ G \\ C_1 \\ \vdots \\ C_i \\ \vdots \\ C_n \end{array} \begin{array}{ccccccc} G & C_1 & \cdots & C_j & \cdots & C_n \\ 0 & 0 & \cdots & 0 & \cdots & 0 \\ w_{1c} & t_{c_{11}} & \cdots & t_{c_{1j}} & \cdots & t_{c_{1n}} \\ \vdots & \vdots & & \vdots & & \vdots \\ w_{ic} & t_{c_{i1}} & \cdots & t_{c_{ij}} & \cdots & t_{c_{in}} \\ \vdots & \vdots & & \vdots & & \vdots \\ w_{nc} & t_{c_{n1}} & \cdots & t_{c_{nj}} & \cdots & t_{c_{nn}} \end{array} \tag{15}$$

3.2.2 Group weighting: Hierarchical clustering

In the process of group weighting, a hierarchical clustering process is implemented to determine the group priorities (Garmendia and Gamboa 2012). This process involves representing each stakeholder j as a point $W_c^j = (w_{1c}^j, w_{2c}^j, \ldots, w_{nc}^j)$ in an n-dimensional weight space, where n is the number of criteria, w_{ic}^j is the evaluation weight of criteria i evaluated by stakeholder j. Each point is considered as the smallest cluster initially.

The subsequent step involves merging the clusters based on Ward's method (Ward 1963), which aims to minimize the total intra-cluster variance. Each point is considered as an individual cluster. The merging of clusters is executed by first computing the distance between each pair of clusters using the squared Euclidean distance. Eq. (16) presents the distance measure between the composite weights w_c from two clusters. The distance is calculated by taking the square of the Euclidean distance between the weight vector of cluster p (W_c^p) and the weight vector of cluster q of (W_c^q). It is the sum of the squared differences between each weight component of the two clusters. Subsequently, as shown in Figure 5, the two clusters with the smallest distance are merged, and this process is repeated until all clusters are merged into a single cluster. Ward's method seeks to create clusters that minimize the loss associated with each cluster, and in each step, all possible combination of cluster pairs is assessed to identify the two clusters that result in the smallest increase in information loss (i.e., the squared Euclidean distance between points).

$$
\begin{aligned}
d_{ij} &= d\left(\{W_c^p\},\{W_c^q\}\right) = \left\|W_c^p - W_c^q\right\|^2 \\
&= \sum_{i=1}^{n} (w_{ic}^p - w_{ic}^q)^2
\end{aligned}
\tag{16}
$$

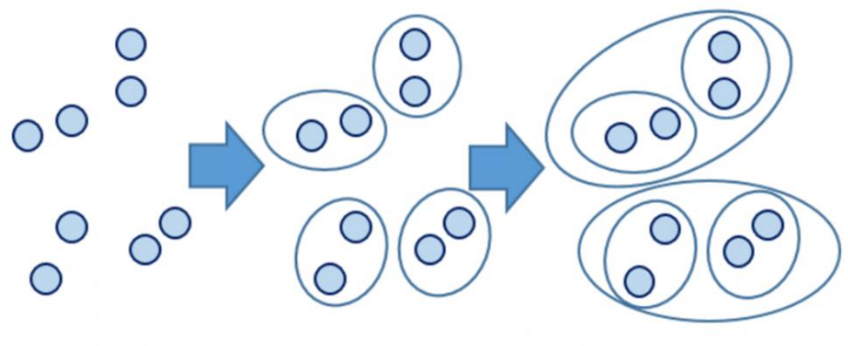


Figure 5. Cluster merging process

Merging of clusters is the key step in hierarchical clustering process. The merging of clusters enables the determination of group priorities, which is critical for effective decision-making (Garmendia and Gamboa 2012). As the number of clusters decreases with each step, the within-cluster variance (i.e., the difference of opinions within the cluster) increases. Thus, it is important to determine an appropriate number of clusters for further analysis. Various statistical tests and methods can be used to determine the number of clusters. However, for sustainability decision-making, the determination of relevant clusters should be based on the researcher's expertise and knowledge acquired through empirical observations (Garmendia and Gamboa 2012). Once the clusters are established, the preference of each stakeholder group (cluster) can be represented by an average set of composite weights.

3.2.3 Alternatives ranking: PROMETHEE II

Following the group weighting, the next step involves the aggregation of criteria weights and performance scores of alternatives for alternatives ranking. To achieve this, PROMETHEE II, a widely recognized MCDM method, is utilized in this study. The PROMETHEE family, including PROMETHEE I and PROMETHEE II, is an outranking method developed by Brans, Vincke et al. (1986). It is a partial-compensatory method and thus enforces a strong sustainability degree of the decision-making process. While PROMETHEE I is used for partial ranking, PROMETHEE II can be used to make a complete ranking of alternatives. In this research, PROMETHEE II is applied to aggregate information and produce full ranking of desalination scenarios on sustainability performance, and it is applied as follows (Brans, Vincke et al. 1986, Kheybari, Javdanmehr et al. 2021):

Step 1: Calculate the deviation between two alternatives within a specific criterion i using:

$$d_i(a,b) = f_i(a) - f_i(b) \text{ for all } i \tag{17}$$

Where $f_i(a)$ and $f_i(b)$ are the performance of alternative a and b on criterion i, $d_i(a,b)$ shows the deviation of the alternatives a and b.

Step 2: Apply the preference functions to the deviations:

$$P_i(a,b) = H_i[d_i(a,b)] \text{ for all } i \tag{18}$$

Where $P_i(a,b) \in [0,1]$ represents the preference of the alternative a compared to the alternative b in criteria i and H_i denotes the type of preference functions for criterion i.

Step 3: Compute the global preference index by aggregating the weighted preferences across all criteria:

$$\pi(a,b) = \sum_i P_i(a,b)w_i \text{ , } \forall(a,b) \in A \tag{19}$$

Where A and w_i indicate a set of alternatives and weight of criteria i respectively. The weights here are provided by BWM-DEMATEL and group weighting. $\pi(a,b)$ represents the intensity of preference of alternative a over alternative b, and when considering simultaneously all the criteria.

Step 4: Compute the flows in the valued outranking graph. Considering alternative a, the leaving flow and entering flow are calculated as below:

$$\text{Leaving flow: } \varphi^{+}(a) = \sum_{x \in A} \pi(a, x) \tag{20}$$

$$\text{Entering flow: } \varphi^{-}(a) = \sum_{x \in A} \pi(x, a) \tag{21}$$

$\varphi^{+}(a)$ and $\varphi^{-}(a)$ respectively express how much a dominates all other alternatives and how much a is dominated by all the other alternatives.

Therefore, the net flow of alternative a is calculated using:

$$\varphi(a) = \varphi^{+}(a) - \varphi^{-}(a) \tag{22}$$

PROMETHEE II provides the complete preorder which is induced by the net flow:

$$\begin{cases} aP_{II}b \ (a \text{ outranks } b) & \text{if } \varphi(a) > \varphi(b) \\ aI_{II}b \ (a \text{ is indifferent to } b) & \text{if } \varphi(a) = \varphi(b) \end{cases} \tag{23}$$

The alternatives can be ranked based on the net flow $\varphi(a)$.

3.3 Data collection

To determine the composite weights of criteria, we designed two questionnaires to collect answers from experts to calculate the direct weights and the interrelationships in criteria. The questionnaires were shared with a diverse group of stakeholders covering desalination, sustainability, and public policy domains. There were 8 experts in total participated in the questionnaires, consisting of 1 policy making researcher, 1 sociological researcher, 2 desalination researchers, 2 environmental researchers, 2 sustainability researchers.

The questionnaire for calculation of direct weights is designed based on the official template of BWM (https://bestworstmethod.com/). As recommended by its developer, the criteria are clustered into four sub-sets (technological, economic, environmental, and social) and evaluated by the experts individually in each sub-questionnaire and integrated in the end. The questionnaire for calculation of the interrelationships in criteria is designed based on DEMATEL technique and adapted from Hsu, Wang et al. (2012). Additionally, a video is made to provide the stakeholders with an instruction on the completion of questionnaires. Detailed information on the questionnaires can be found in Appendix B.

Due to the large number of criteria in the case study, the DEMATEL questionnaire contains an excessive number of questions and thereby it is time-consuming for completion. This posed a big challenge to collect answers from external experts, considering the limitations of this master thesis project. Therefore, the data collection for the interrelationships in criteria was carried out internally, by decision-makers involved in the project. In the preliminary processing of the answers, those from DEMATEL questionnaire are used to construct an average direct influence matrix. It is then combined with different direct weights obtained from experts' responses to the BWM questionnaire to form the composite direct influence matrices for the calculation of composite weights in BWM-DEMATEL.

3.4 Selection of preference functions in PROMETHEE II

As described in Section 3.2.3, preference function is required for each criterion in step 2 of PROMETHEE. Figure 6 summarizes the six types of preference functions and the parameters to be fixed. $H(d_i)$ presents the preference between two alternatives in each criterion, where d_i is the difference of performance score between two alternatives in criteria i. q_i and p_i denote the indifference and preference thresholds in criteria i respectively.

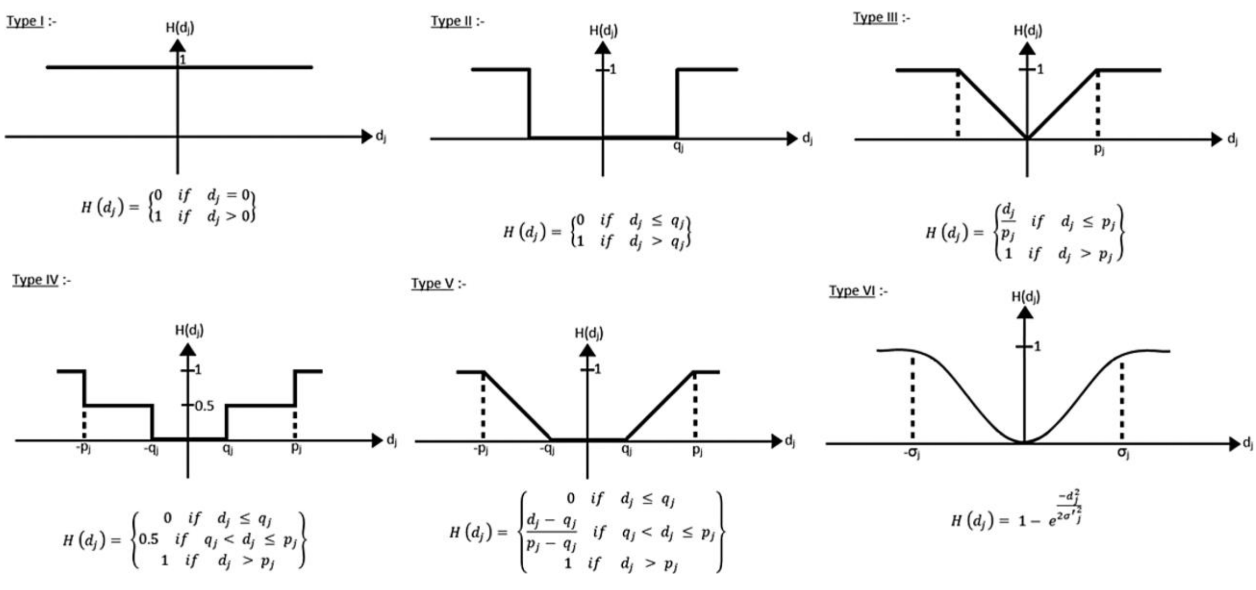


Figure 6. Types of preferences functions in PROMETHEE (Vivekh, Sudhakar et al. 2017)

The selection of a preference function depends on the scale of the underlying criteria (Mareschal 2018) (check Appendix C for the specific principles). In accordance with the selected preference function, the indifference and preference thresholds in criteria i are set to be 5% and 10% respectively of the minimum of the absolute value in the performance scores of criteria i as a practical approximation (Wulf, Zapp et al. 2021). Considering the criteria selected for the case study, the preference functions selected and defined thresholds are presented in Table 5.

Table 5. Preference functions and thresholds in the case study.

	Criteria	Unit	Preference function	q	p
Technological	Energy consumption	Mwh/year	Type V	140	280
	Quantity of water produced	m^3/year	Type V	2500	5000
	Resource efficiency	(%)	Type III	-	2.5
	Brine production	ton/year	Type V	0	0
Economic	Levelized cost	€/m^3	Type V	1	2
	CAPEX	€	Type V	1378000	2756000
	OPEX	€/year	Type V	660	1320
	Production efficiency	%	Type III	-	0.02
Environmental	Carbon dioxide emission	(ton CO_2-Equ)	Type V	277500	555000

	Water footprint	m^3/year	Type V	0	0
	Human toxicity	-	Type III	-	0
Social	Operational complexity	-	Type I	-	-
	Safe and healthy conditions	-	Type I	-	-
	Local employment	-	Type I	-	-
	Level of aesthetic acceptability	-	Type I	-	-

3.5 Software and tools utilization

Various software and tools are utilized in this study to support the modeling process and data analysis. We applied the linear BWM solver developed by Dr. J. (Jafar) Rezaei to calculate the direct weights of criteria in BWM method (https://bestworstmethod.com/). In addition, we used VISUAL PROMETHEE in the ranking process to generate visualized decision results (promethee-gaia.net). With all the required inputs (criteria, alternatives, weights, performance scores, and thresholds), ranking results can be calculated automatically in VISUAL PROMETHEE. The software and tools used in this research are both freely available for academic research.

4. Results and discussion

This chapter presents the evaluation on the results of the case study implementation, which comprises of 7 sections. Section 4.1 presents an analysis of the interdependences in the desalination system, which is obtained from BWM-DEMATEL. Section 4.2 offers an overview of the individual weights from each stakeholder. In Section 4.3 the comparisons of weights in different clusters are performed. In Section 4.4 the effects on the weights of incorporating interdependence among criteria are analyzed. In Section 4.5 the ranking of desalination scenarios are shown. In Section 4.6 the effects on the ranking of incorporating interdependence among criteria are analyzed. Finally, the characteristics of BWM-DEMATEL are summarized and the research questions are answered in Section 4.7.

4.1 Influential relationships in desalination systems

The influences in criteria are required for the acquisition of composite weights. Following the steps described in Section 3.2.1, the influential relationships of the criteria are calculated in the DEMATEL framework based on the average values derived from the responses of two decision makers (DM 1 and DM 2). Figure 7 shows the influential strength of each criterion, which indicates the relative importance of criteria on the influential relationships in the system. For example, OPEX has the influential strength (0.096) on the system, considering both the total influences given and received. On the contrary, the level of aesthetic acceptability has the lowest influential strength (0.046). The influential strength was also used as criteria weights for decision making in some research (Si, You et al. 2018).

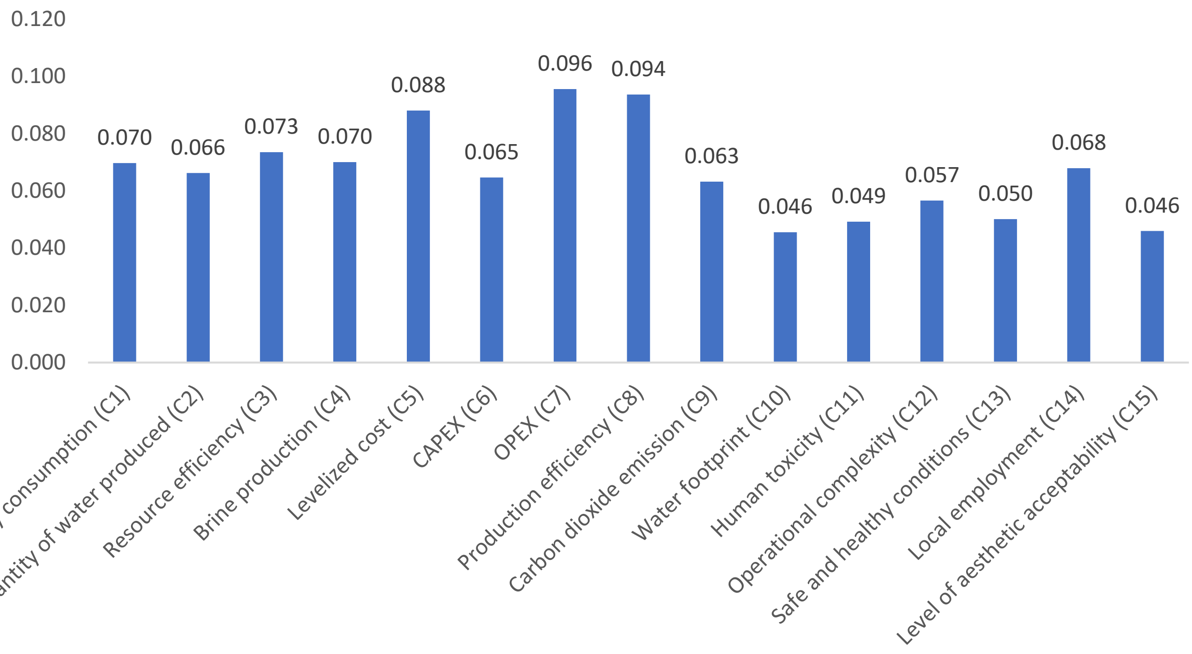
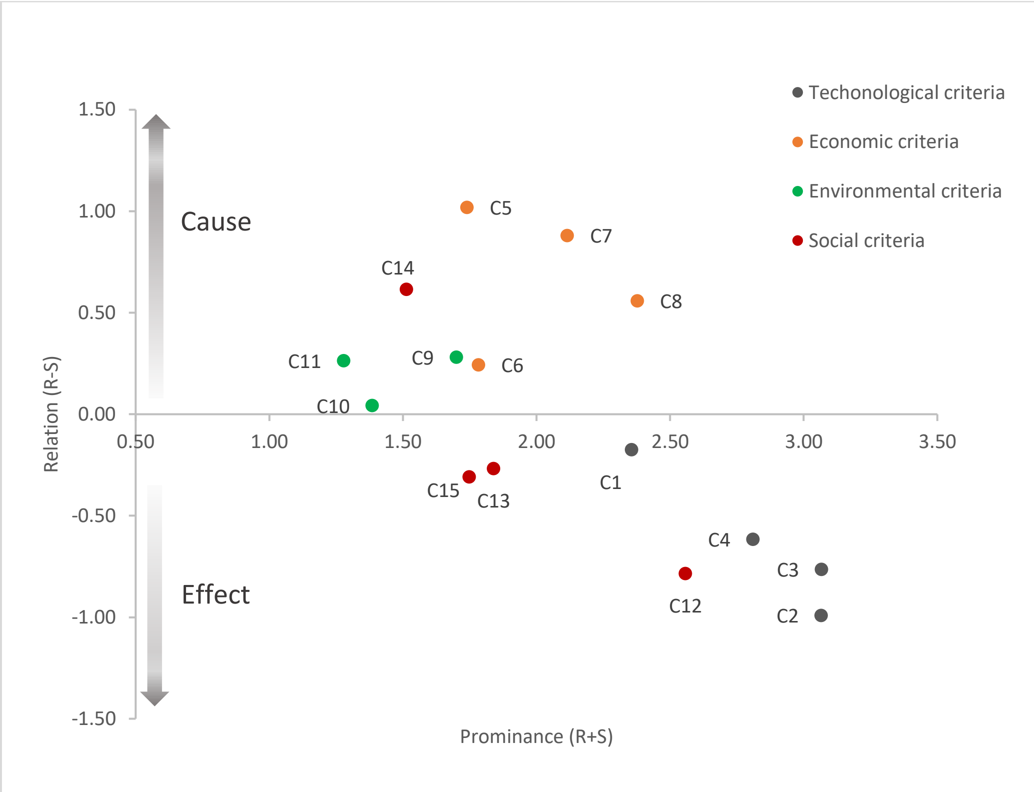


Figure 7. Influential strength of criteria

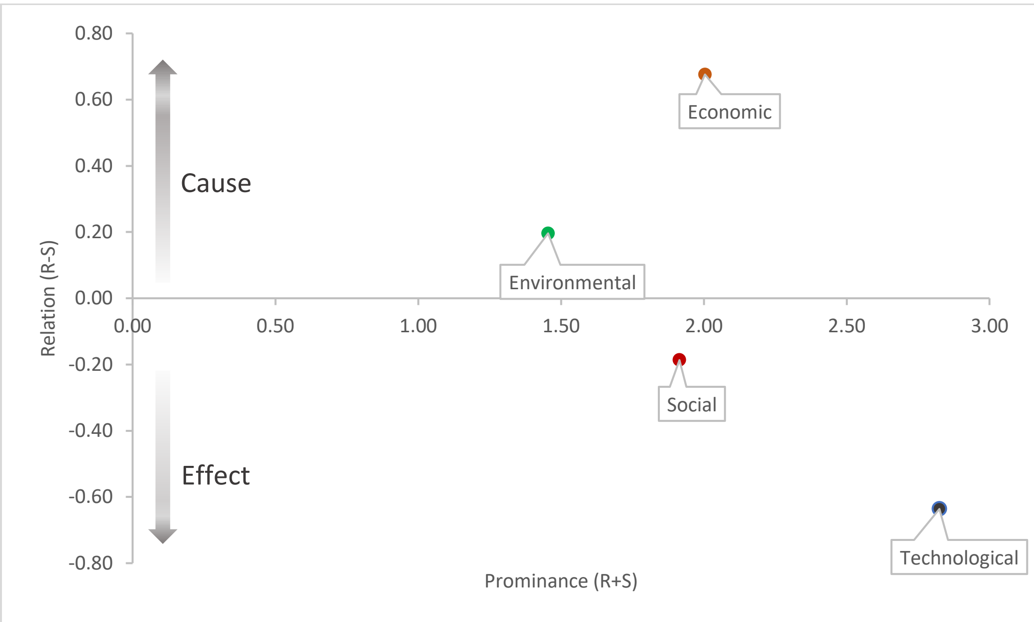
Table 6 presents the sum of influences given and received on criteria, where R is the sum of given influences, S is the sum of received influences. The prominence (R+S) and relation (R-S) of criteria and dimensions are illustrated by influential relation maps (IRM) in Figure 8. The IRM for dimensions is based on the average R+S and R-S of criteria in each dimension. Figure 8(a) indicates that Levelized cost (C5) is the strongest cause factor for desalination, which is most able to influence the other criteria. On the other hand, Quantity of water produced (C2) is the strongest effect factor and can be largely affected by other criteria. In terms of dimensions, Figure 8(b) shows that the largest prominence (R+S) is for technological dimension (2.82), which means that it has the largest total influence degree within dimensions. Besides, economic and environmental dimensions are identified as driven factors in desalination since they have high relation. This indicates that they are constraints for a desalination project, which is in line with the reality of desalination industry. The improvement of economic and environmental performance yields positive effects on the overall performance of all four dimensions. On the other hand, social and technological dimensions are impacted by other dimensions since they have high prominence but low relation. Their performances cannot be improved directly but needs considerations on their constraints. The influential relationships can facilitate the comprehension of the roles played by various factors in a desalination system, thereby offering valuable insights into potential improvements in sustainability of desalination.

Table 6. The sum of influences given and received on criteria.

	R	S	R+S	R-S
C_1	1.09	1.27	2.36	-0.17
C_2	1.04	2.03	3.07	-0.99
C_3	1.15	1.92	3.07	-0.76
C_4	1.10	1.71	2.81	-0.62
C_5	1.38	0.36	1.74	1.02
C_6	1.01	0.77	1.78	0.24
C_7	1.50	0.62	2.12	0.88
C_8	1.47	0.91	2.38	0.56
C_9	0.99	0.71	1.70	0.28
C_{10}	0.71	0.67	1.39	0.04
C_{11}	0.77	0.51	1.28	0.26
C_{12}	0.89	1.67	2.56	-0.79
C_{13}	0.79	1.05	1.84	-0.27
C_{14}	1.06	0.45	1.51	0.62
C_{15}	0.72	1.03	1.75	-0.31



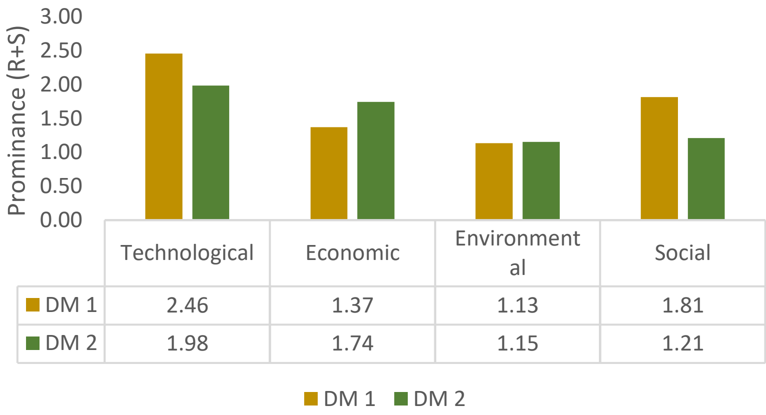
(a)



(b)

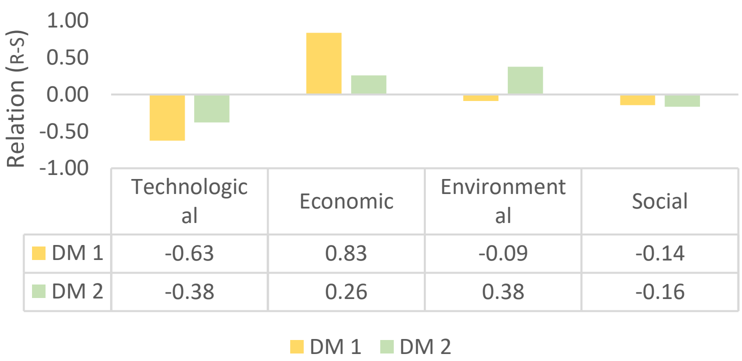
Figure 8. Influential Relation Maps: (a) IRM at criteria level. (b) IRM at dimension level.

It is important to note that there is a difference between responses from DM 1 and DM 2. Figure 9 shows the prominence (R+S) and relation (R-S) of dimensions calculated only from responses of DM 1 and DM 2 respectively. It can be found that the environmental dimension has a negative relation (R-S) for DM 1, indicating that it is an effect factor for desalination. On the contrary, it turns to be a cause factor with a positive relation for DM 2. Therefore, diverse opinions can be expected from stakeholders on the interdependency in desalination according to their background, knowledge, and expertise. The diverse opinions are limited in this study since not a big group of stakeholders are involved in the evaluation of interdependency in desalination. As described in Section 3.2.1, the interdependence among criteria should be calculated based on the opinions of each stakeholder, and then combined with the direct weights from them to indicate the composite weights. However, an average direct influence matrix was derived from answers of DM 1 and DM 2 and combined with direct weights to calculate the composite weights. This doesn't reflect the real situation and might overestimate or underestimate the impact of the independences on the decision-making process.



	Technological	Economic	Environmental	Social
DM 1	2.46	1.37	1.13	1.81
DM 2	1.98	1.74	1.15	1.21

(a)



	Technological	Economic	Environmental	Social
DM 1	-0.63	0.83	-0.09	-0.14
DM 2	-0.38	0.26	0.38	-0.16

(b)

Figure 9. Differences in prominence and relation of dimensions between DM 1 and DM 2. (a) Prominence of dimensions. (b) Relation of dimensions.

4.2 Composite weights of criteria along the stakeholders

Following the procedure of BWM-DEMATEL which is described in Section 3.2.1, the direct weights and composite weights are calculated at the individual level. The composite weights are illustrated in Figure 10 (specific values are given in Appendix E). It shows the dispersion of composite weights assigned to each criterion by the stakeholders, whose background are given in Table 7. It can be found that although the opinions are relatively concentrated on most criteria, extreme opinions present in some criteria. For example, the greatest differences in individual weights are related to the importance associated with OPEX (criteria 7), where the standard deviation (S.D.) is 10.6%. Additionally, the weight of OPEX (35.7%) from a desalination researcher (stakeholder 8) is 4.4 times higher than the average value (8.1%). Such values are extreme and away from the common consensus but should not be overlooked in the decision-making process by averaging the opinions, as explained in Section 2.2.2. Therefore, it calls for a hierarchical clustering to group these individual weights to show the diversities in social preferences, instead of an achievement of consensus.

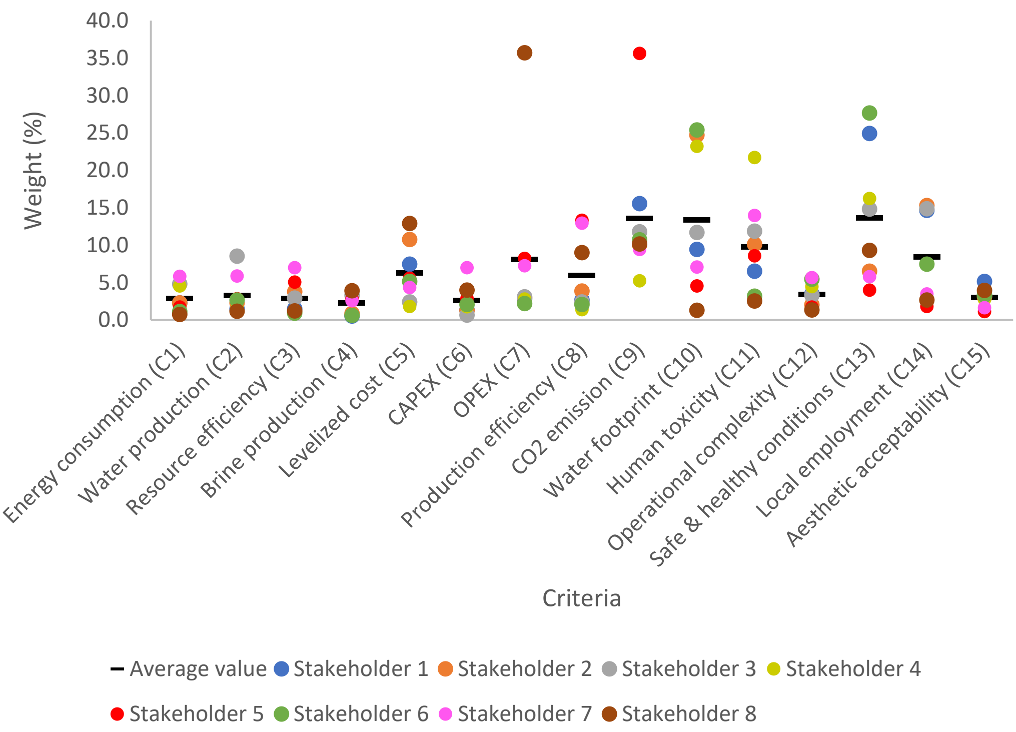


Figure 10. Diagram of dispersion of individual composite weights

As presented in Table 7, the decision-making process involves a limited number of stakeholders, amounting to only 8 individuals. The presence of a small sample size may contribute to the emergence of extreme opinions. To enhance the persuasiveness of such extreme opinions, a broader range of stakeholders should be involved. Besides, while researchers in different fields participated in the decision-making process, there is still a lack in terms of stakeholder diversity. In particular, the exclusion of engineers and members of the local community with valuable insights, could potentially hinder the overall quality of the decision-making process.

Table 7. Background of stakeholders in the study.

Stakeholder name	Background
Stakeholder 1	Sociological Researcher
Stakeholder 2	Desalination Researcher
Stakeholder 3	Environmental researcher
Stakeholder 4	Sustainability Researcher
Stakeholder 5	Environmental researcher
Stakeholder 6	Sustainability Researcher
Stakeholder 7	Policy making Researcher
Stakeholder 8	Desalination Researcher

4.3 Weight Clusters under diverse preferences

4.3.1 Stakeholder Clusters in group weighting

The determination of group weights is based on a hierarchical clustering process described in Section 3.2.2. The dendrograms presented in Figure 11 illustrates the hierarchical merging of stakeholders and groups based on the similarities of their priorities, where the values of x-axis represent the distance between clusters. At each step, the number of clusters decreases and the within-cluster variance increases (distance). The red cutting line results in three clusters for this study based on the potential similarities and discrepancies of the individual weights. The clusters are visualized using different colors in Figure 11, where the orange cluster (cluster 1) represents the majority opinions, and the green (cluster 2) and blue (cluster 3) clusters represent two minority groups. Specifically, cluster 2 consists of an environmental researcher and a policy making researcher (stakeholder 5 and 7), while cluster 3 consists of a desalination researcher (stakeholder 8).

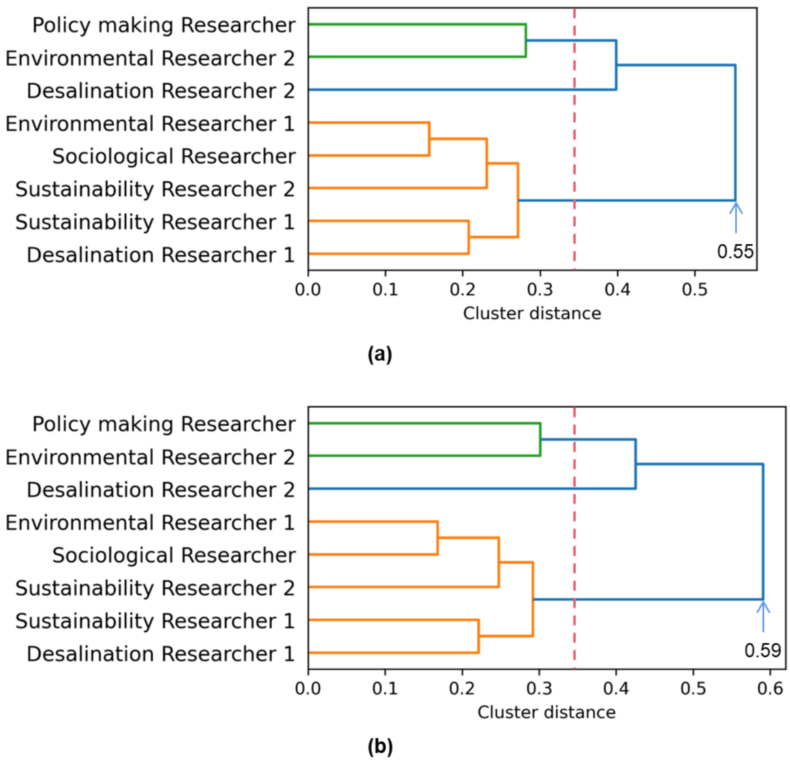


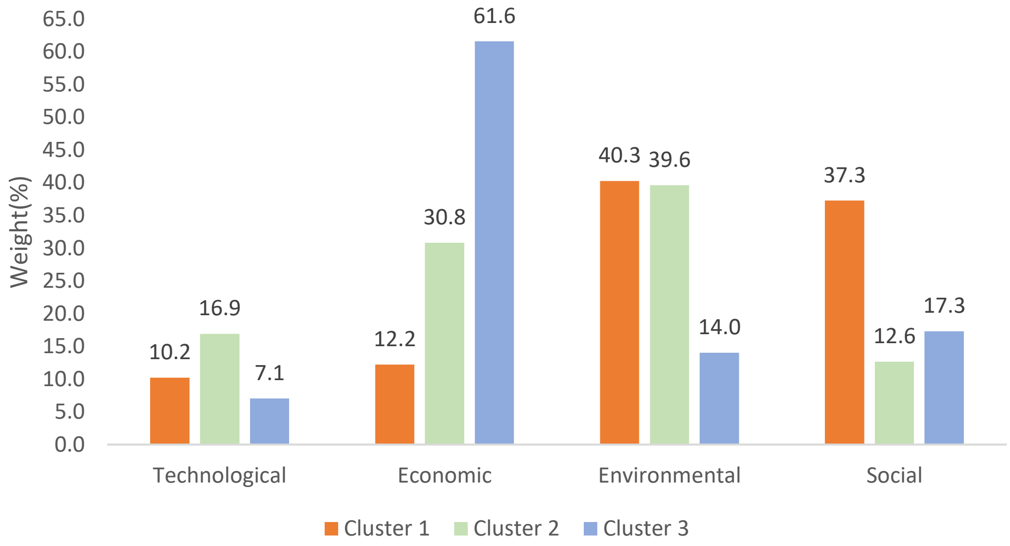
Figure 11. Dendrograms of clusters according to group weights. (a) Hierarchical clustering Dendrogram of Composite weights; (b) Hierarchical clustering Dendrogram of Direct weights.

The clustering outcomes for both direct weights and composite weights are similar. This observation is expected as the weight determination process incorporates the same average influence matrix for each individual weight set. As a result, considering the interdependencies in criteria does not alter the final clustering results. However, it does have an impact on the hierarchical clustering. The maximum clustering distance in composite weights (0.55) is smaller than in direct weights (0.59). This suggests a reduction of variation in stakeholders’ judgements on the importance of criteria, which means that the opinions are more concentrated and less conflicting by considering the interdependency in desalination.

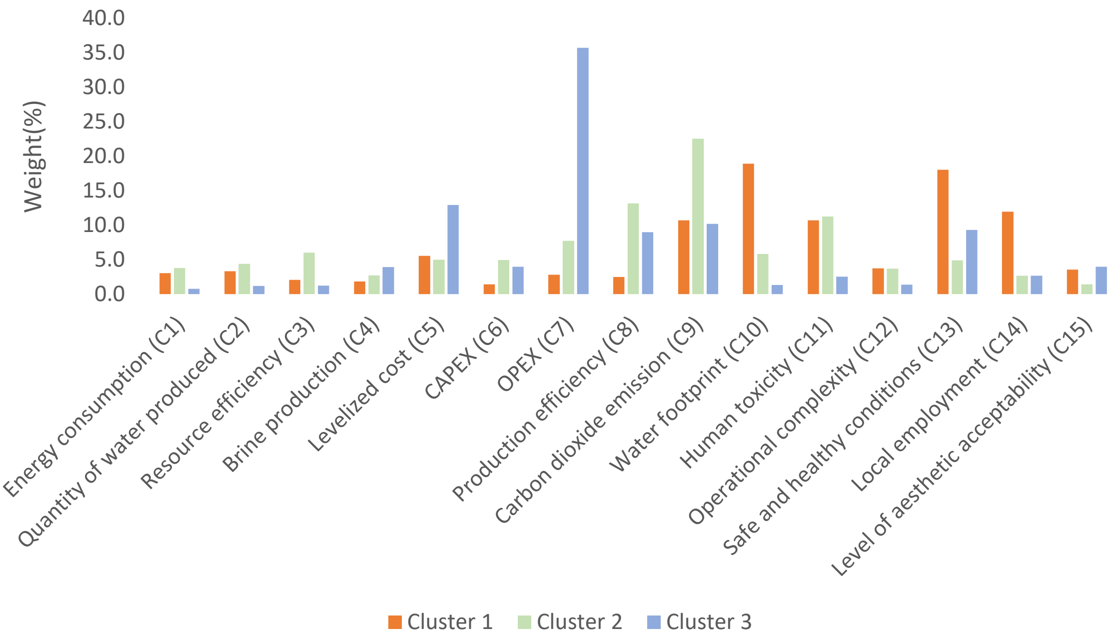
4.3.2 Group weights in different clusters

The group weights are calculated by averaging the individual weights in each cluster, and the diversities in the group weights reflect the preferences of stakeholders regarding sustainable desalination. Cluster 1 support an environmental and social oriented sustainability for desalination, while cluster 2 prioritizes environmental and economic aspects. On the other hand, cluster 3 primarily focuses on economic considerations.

Figure 12(a) shows the composite weights of dimensions in the three clusters. In both cluster 1 and cluster 2, the environmental dimension is considered as the most important, with weights of 40.3% and 39.6% respectively. However, cluster 1 places greater emphasis on the social dimension (37.3%), whereas cluster 2 assigns more importance to the economic dimension (30.8%). In contrast, cluster 3 displays a distinct perspective where the economic dimension holds the highest importance for desalination (61.6%), accompanied by relatively lower weights for the other three dimensions. This viewpoint is expressed by a desalination researcher who specifically highlights the importance of OPEX with a weight of 35.7%. It may be worthwhile to engage in further communication with this stakeholder to obtain additional insights. By considering the backgrounds of stakeholders within each cluster, these findings provide valuable insights into the ranking results from different clusters. These insights facilitate a better understanding of the prioritization of desalination scenarios, guiding towards well-informed decisions on the sustainability of desalination.



(a)



(b)

Figure 12. Group weights in different clusters. (a) composite weights of the four dimensions; (b) composite weights of criteria.

4.4 Criteria weights: Direct weight vs Composite weight

In the weight determination process through BWM-DEMATEL, the direct weights and composite weights of each cluster are calculated. And it can be found that integrating the interdependences among criteria into weight determination can affect the relative importance of criteria. Figure 13 shows the direct weights and composite weights of the four dimensions in the majority opinions (cluster 1). Meanwhile, Table 8 provides the mean weights and S.D. of the individual weights within cluster 1. The mean values represent the group weights of cluster 1, while the S.D. of the individual weights reflects the level of dispersion among the opinions expressed by stakeholders within cluster 1. It can be found that by considering the interdependences in criteria, there is an increase of 10.42% and 12.47% in the weights assigned technological and economic dimensions. Conversely, the weight of environmental dimension slightly decreases by 4.34%, while the weight of social dimension remains nearly unchanged (from 37.76% to 37.27%). Hence, the integration of interdependencies among factors (criteria and dimensions) yields varying outcomes within the system. A more realistic reflection on the importance of each factor is provided by the composite weights, which is different from the weight calculated based on the assumption that criteria are independent. With this information, it becomes possible to determine the critical aspects that require optimization for enhancing the sustainability of a desalination project.

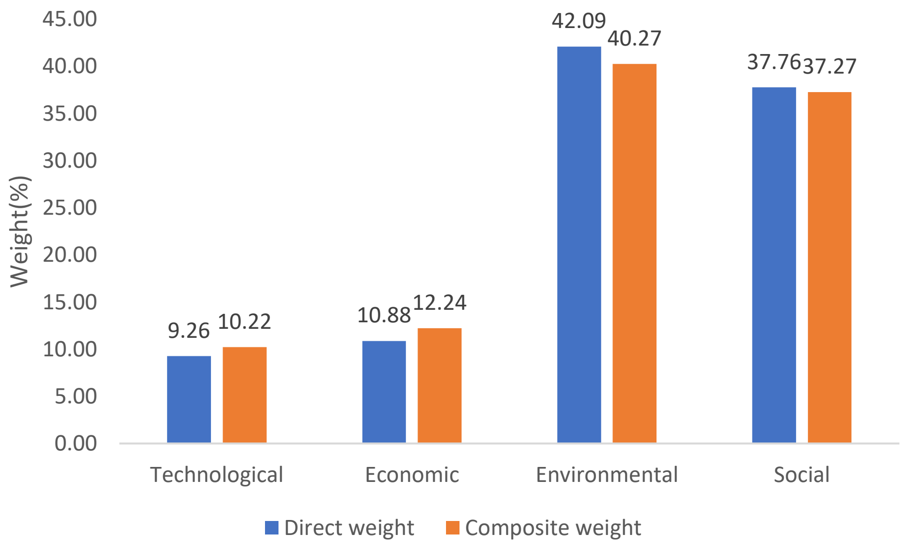


Figure 13. Direct and composite weights of dimensions in cluster 1

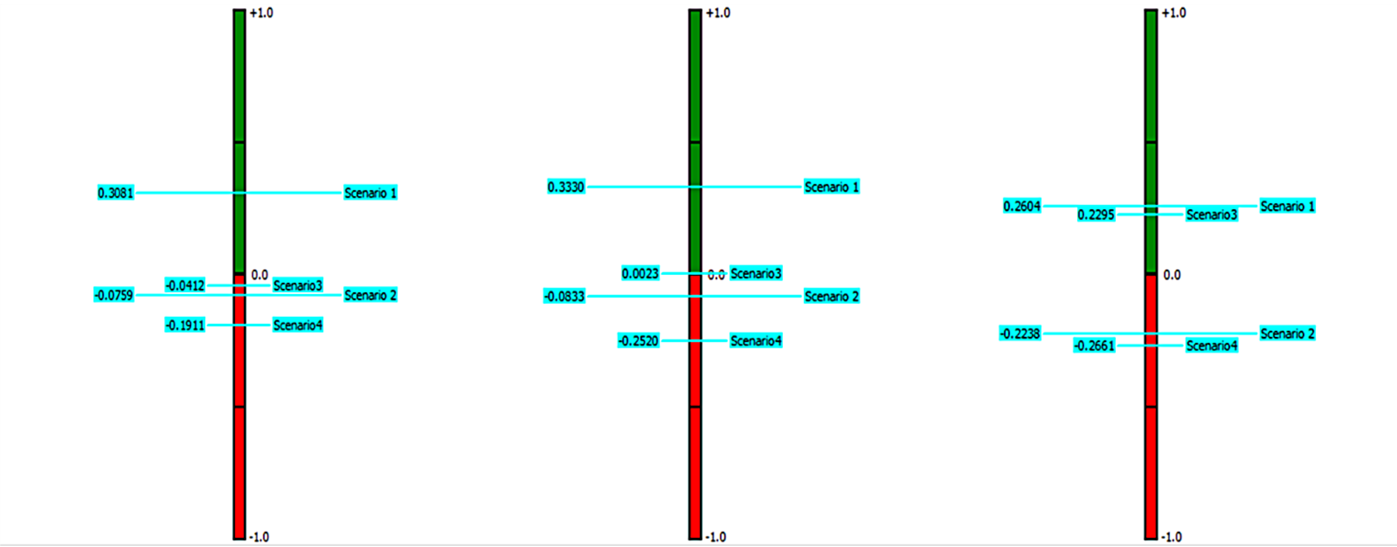
Table 8. Differences in direct and composite weights of dimensions in cluster 1.

	Direct weight (%)		Composite weight (%)		Relative variation (%)	
	Mean	S.D.	Mean	S.D.	Mean	S.D.
Technological	9.26	0.38	10.22	0.33	10.42	-6.38
Economic	10.88	0.23	12.24	0.21	12.47	-4.41
Environmental	42.09	0.64	40.27	0.55	-4.34	-7.20
Social	37.76	0.90	37.27	0.78	-1.31	-6.83

With respect to the dispersion of individual weights within the cluster, the incorporation of interdependencies results in a decrease in the S.D. across all four dimensions. This reveals that the opinions are more concentrated when considering the interdependency. In addition, with the same influence matrix combined, the impact of integrating the interdependency varies among different clusters (check Appendix F for detailed information). It indicates that the extent of impact on the weights depends not only on the strength of the independence in criteria but also on the direct weights, which can be supported by Eq. (1).

4.5 Ranking of Alternatives Resulting from group weights

Figure 14 presents the rankings of alternatives with their φ scores according to the composite weights of each cluster. It can be observed that consistent rankings are obtained across different clusters, with Scenario 1 being identified as the most sustainable desalination scenario, followed by Scenario 3, Scenario 2, and Scenario 4 in sequential order. The ranking results are robust despite the varying sustainability orientations among stakeholders as indicated by the composite weights in clusters. This can be attributed to the fact that the ranking is not so sensitive to criteria weights in this case study. The ranking not only depends on the criteria weights, but also the performance scores of alternatives and the defined thresholds in the ranking process. These factors largely affect the final rankings in this study.



(a) Cluster 1 (b) Cluster 2 (c) Cluster 3

Figure 14. Rankings of desalination scenarios in different clusters (from VISUAL PROMETHEE). (a) Ranking of desalination scenarios according to composite weights in cluster 1; (b) Ranking of desalination scenarios according to composite weights in cluster 2; (c) Ranking of desalination scenarios according to composite weights in cluster 3.

However, although the overall rankings are consistent in all the clusters, variations are observed in the ranking process. The overall ranking is determined by the net flow φ of each alternative which represents the gap between leaving flow φ^+ (strength) and entering flow φ^- (weakness). These strengths and weaknesses of each alternative differ based on the weights assigned by different clusters. For example, the performance on economic dimension is a weakness for Scenario 1 compared to other desalination scenarios in cluster 1 and 2. However, in cluster 3, Scenario 1 is regarded as having a strength in the economic dimension based on the assigned weights. The detailed information can be found in Appendix G.

The economy oriented weights of cluster 3 significantly influences the sustainability performance of alternatives. Consequently, the gap between Scenario 1 and Scenario 3 within cluster 3 is noticeably narrower compared to that observed in cluster 1 and cluster 2, as illustrated in Figure 14. The minute discrepancy between Scenario 1 and Scenario 3 makes their comparison inconclusive. Therefore, an in-depth insight into the performance of alternatives in PROMETHEE ranking in cluster 3 is given by Figure 15. The left column represents the order of alternatives based on φ^+, and the right column represents the order based on φ^-. The values of φ^+ and φ^- of each alternative are given in Table 9. It can be found that Scenario 3 ($\boldsymbol{\varphi}^-$= 0.2201) exhibits fewer weaknesses compared to Scenario 1 ($\boldsymbol{\varphi}^-$= 0.2280), while the strength of Scenario 3 ($\boldsymbol{\varphi}^+$= 0.4496) is lower than that of Scenario 1 ($\boldsymbol{\varphi}^+$= 0.4885). These findings indicate a trade-off between weaknesses and strengths when comparing Scenario 1 and Scenario 3. While Scenario 3 demonstrates a slight advantage in terms of fewer weaknesses, it comes at the cost of a relatively lower strength compared to Scenario 1. Figure 16 shows the specific strengths and weaknesses of each alternative on each criterion. It can be found that the economic strengths and weaknesses of Scenario 1 are enlarged due to the high weights of economic criteria in cluster 3. As a result, it performs worse than Scenario 3 in terms of overall weakness ($\boldsymbol{\varphi}^{-}$). This ranking reversal explains the minimal differences in φ (0.0309) between Scenario 1 and Scenario 3 in cluster 3, as depicted in Figure 14. It further suggests that Scenario 1 and Scenario 3 may be incomparable in terms of their sustainability performance, which is not observed in cluster 1 and cluster 2.

Table 9. Values of $\boldsymbol{\varphi}$, $\boldsymbol{\varphi}^{+}$, and $\boldsymbol{\varphi}^{+}$ of desalination scenarios in cluster 3.

Alternative	$\boldsymbol{\varphi}$	$\boldsymbol{\varphi}^{+}$	$\boldsymbol{\varphi}^{-}$
Scenario 1	0.2604	0.4885	0.2280
Scenario 2	-0.2238	0.2751	0.4989
Scenario 3	0.2295	0.4496	0.2201
Scenario 4	-0.2661	0.2507	0.5169

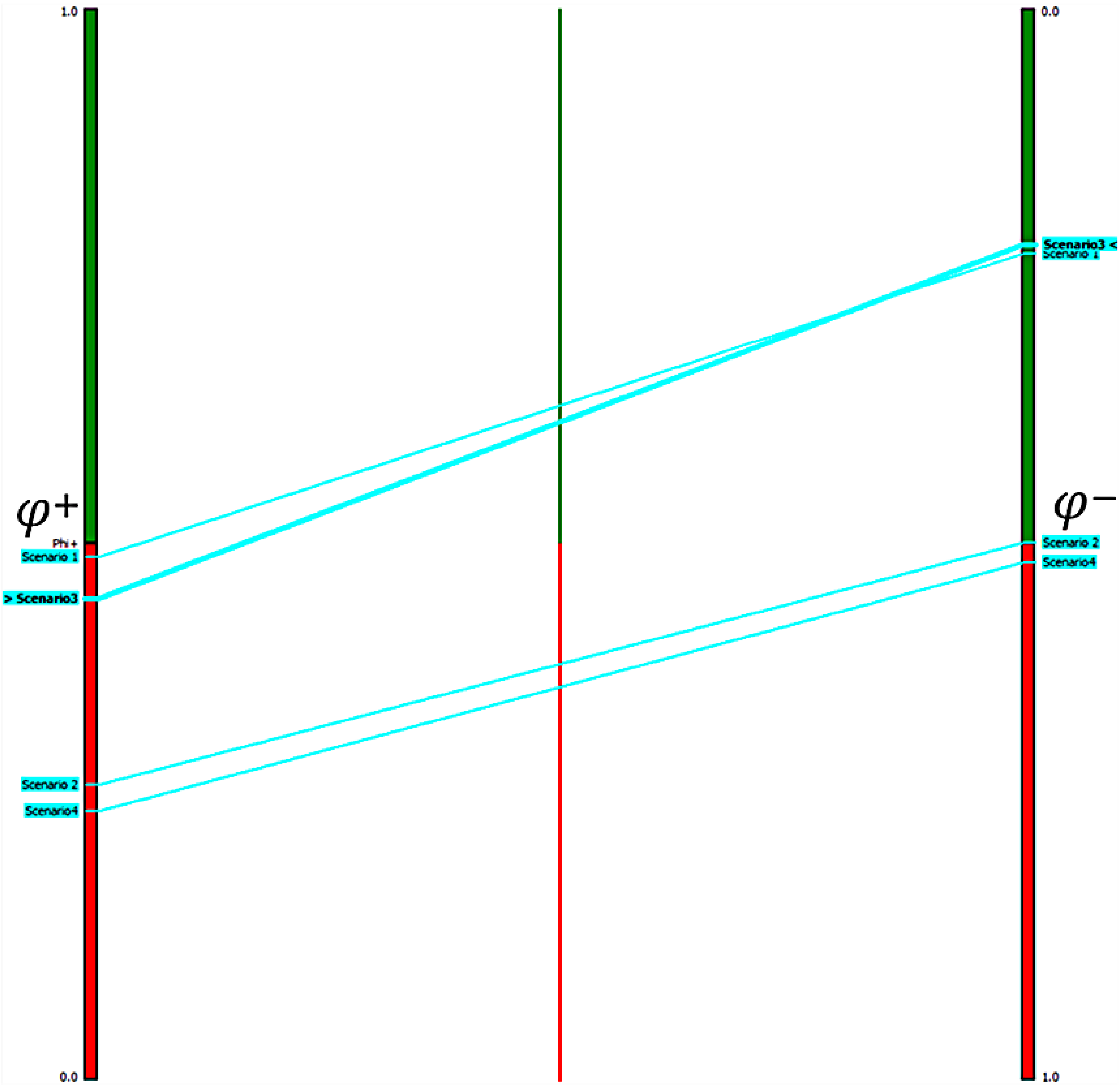


Figure 15. Alternatives ranking of φ^+ and φ^- in cluster 3 (From VISUAL PROMETHEE)

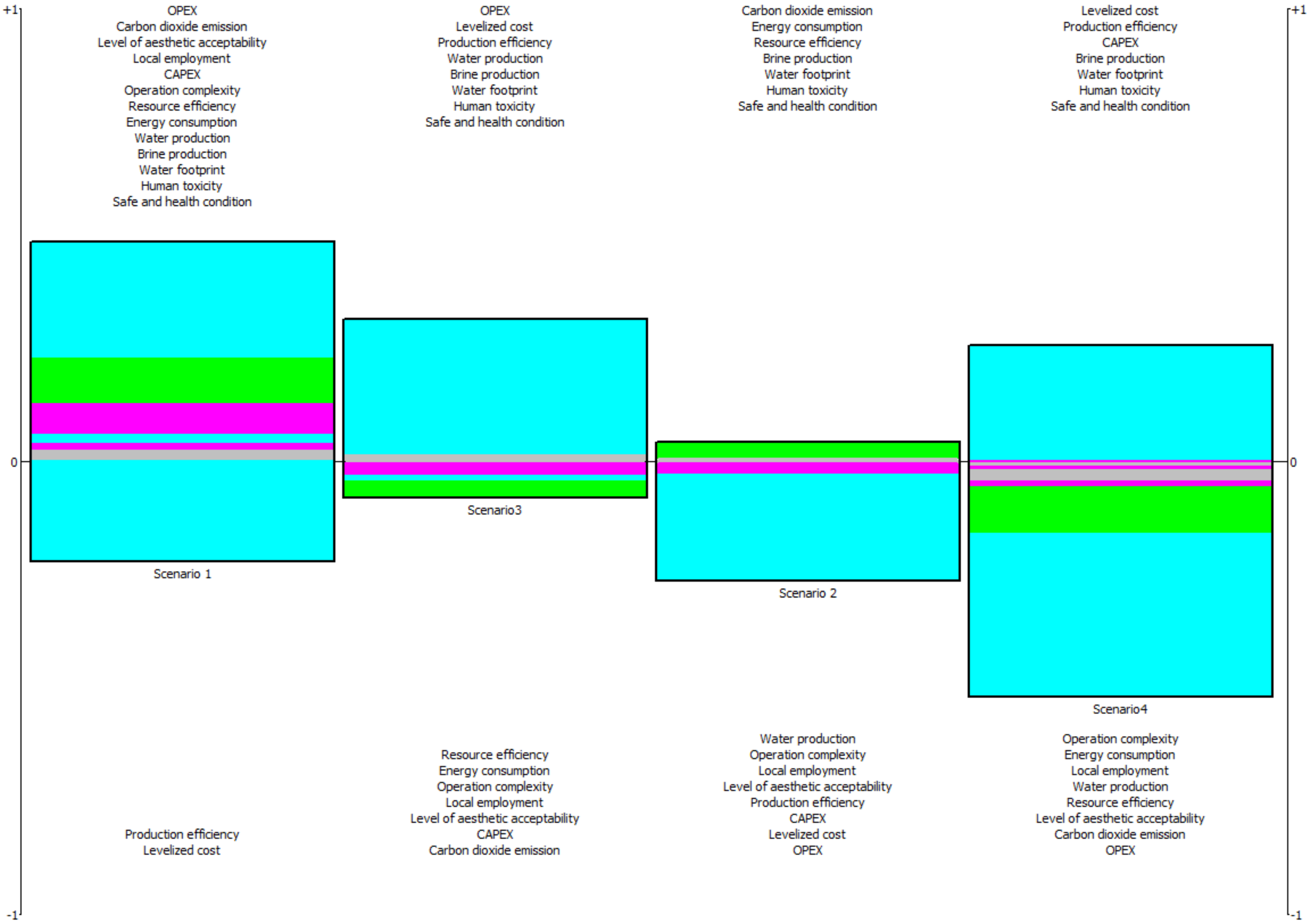


Figure 16. PROMETHEE Rainbow in cluster 3 (From VISUAL PROMETHEE).

Note: the PROMETHEE Rainbow reveals the strengths and weaknesses of each alternative in each criterion. Criteria in each dimension are represented by various colors. Grey slices represent technological criteria, blue slices represent economic criteria, green slices represent environmental criteria, and purple slices represent social criteria. Each slice corresponds to the contribution of the criterion to the sustainability performance (φ score) of the alternaive considering the weight of the criterion. Positive slices represent the advantageous criteria, and negative slices represent the disadvantageous criteria. The bar length indicates the extent of advantages and disadvantages. This way the sum of the positive slices minus the sum of the negative ones is equal to the Phi net flow score of the alternative.

4.6 Alternatives rankings: Direct weight vs Composite weight

This section presents a comparison of ranking results according to direct weights and composite weights. In all three clusters, the incorporation of interdependences among criteria doesn't result in a ranking reversal. The rankings of alternatives remain consistent with those based on direct weights. The effect of interdependence among criteria on the alternatives ranking is resulted from the variations in criteria weights. The consistent ranking results indicate that the alternatives ranking is not sensitive to the criteria weights in this case study. Instead, it is more affected by other factors, such as the performance scores, and the preference and indifference thresholds in PROMTHEE.

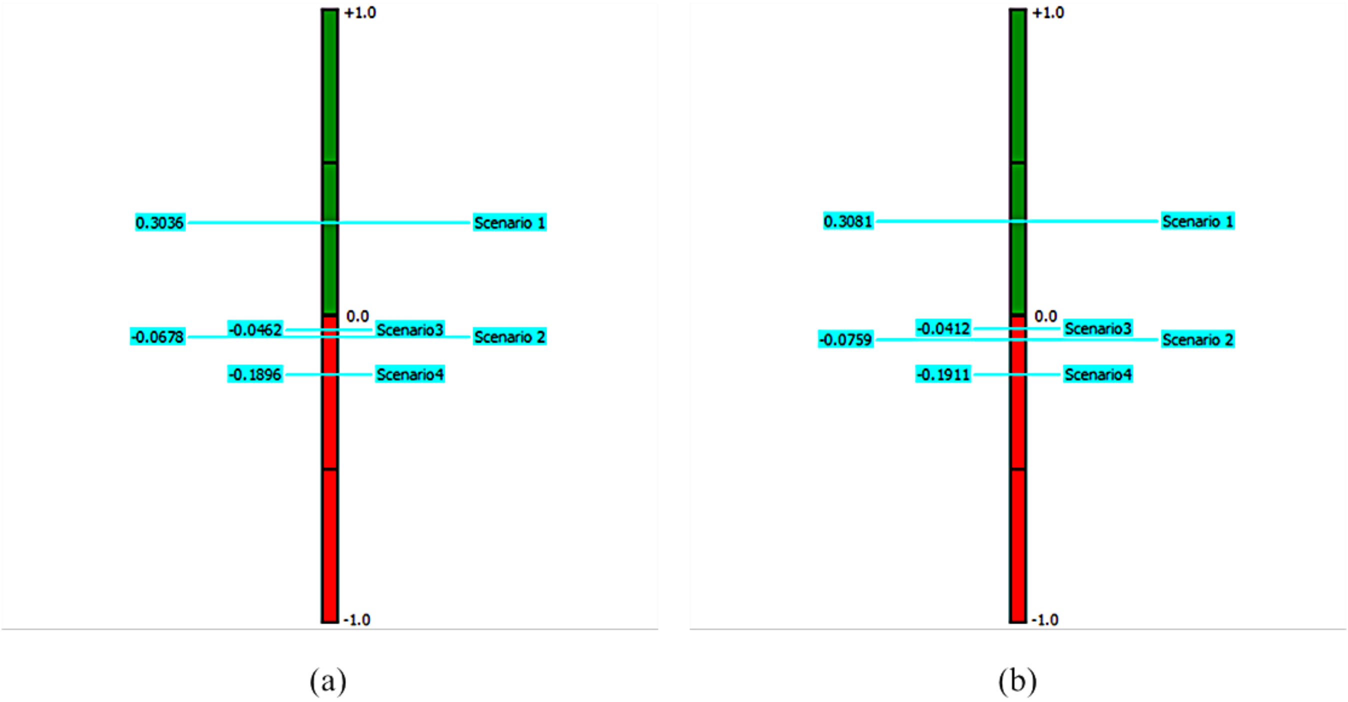


Figure 17. Alternatives rankings in cluster 1 according to direct weights and composite weights (From VISUAL PROMETHEE).

(a). Alternatives ranking based on direct weights. (b). Alternatives ranking based on composite weights.

However, the sustainability performance ($\boldsymbol{\varphi}$ score) varies when incorporating the interdependences. Figure 17 presents the differences rankings of alternatives with their φ scores according to the direct weights and composite weights in cluster 1, which is the majority opinions in stakeholders. The results reveal that after incorporating the interdependences, the sustainability performance of Scenario 1 slightly increases from 0.3036 to 0.3081. In addition, the gap on sustainability performance between Scenario 2 and Scenario 3 increases from 0.0261 to 0.0347. This indicates the significance of considering the interdependences in the decision-making process. Despite that in this case study the variation doesn’t affect the final ranking due to the influence of the other factors on the ranking, it can be expected that the interdependences can have significant influence on the decision problems which are sensitive to the criteria weights.

4.7 The application of BWM-DEMATEL

In summary, the application of BWM-DEMATEL method provides a valuable framework to analyze the interrelationships in the system, as well as to integrate them into the decision-making process. It enables the identification of important factors for a sustainable option and examines of their dependences and feedbacks. By incorporating interdependencies, this method enhances understanding of criteria and thereby varying the dispersion of stakeholder opinions. The impact of interdependency on the final decision is realized by altering the weights assigned to the criteria. However, its influence is restricted in cases where the decision is not sensitive to the variations in criteria weights.

BWM-DEMATEL is characterized by its complexity in terms of data collection. The numerous pairwise comparisons involved can make the process time-consuming and highly subjective. In cases where the ranking of alternatives is not significantly affected by variations in weights, implementing BWM-DEMATEL may not yield different results compared to simpler methods without considering interdependences, like AHP and BWM. Considering the associated costs, it raises questions about the practicality of adopting BWM-DEMATEL in such projects.

Overall, while the BWM-DEMATEL method offers valuable insights into decision problems, it is important to carefully evaluate its applicability based on the specific context and trade-offs between complexity and potential benefits.

5. Limitations and Recommendations

- Unsolved problem on the incorporation of interdependence among criteria

In Section 3.2.1, a novel weighting method (BWM-DEMATEL) is developed to incorporate the interdependence among criteria into the decision-making process. As discussed in the literature review, there are two main problems in current weighting methods with respect to the interdependency: the missing of direct influence of criteria on the goal, and the directionality of influence. While the former one is addressed in the proposed method, the directionality of influence remains a challenge to the algorithm. BWM-DEMATEL calculates the influences based on a convertible influence matrix. The negative influence value would destroy the convergence of the matrix, indicating the infeasibility of considering the directionality in the proposed method. Therefore, it is recommended to explore the possibility of using different algorithms to incorporate the interdependence among criteria, so that the directionality of influence can be well addressed.

- Drawbacks of BWM-DEMATEL for weight determination

Similar to ANP and DEMATEL, BWM-DEMATEL requires a large number of pairwise comparisons between criteria to construct the influence matrix. Given n criteria for a decision problem, $n^2 + n - 3$ comparisons are needed for weight determination. This significantly increases the complexity of the weighting procedure. As a result, the communication with stakeholders would be very difficult. In this study, it took one hour to complete the questionnaires for BWM-DEMATEL, which made it a challenge to collect sufficient answers from stakeholders. In addition, the lots of pairwise comparisons would result in a large subjectivity in the criteria weights, as well as a high risk of inconsistency in the judgements.

It is possible to determine the interdependence among criteria through the correlations in the performance scores of alternatives in each criterion. Li, Ren et al. (2020) used combined DEMATEL and GRA for weight determination. The interdependence among criteria was calculated based on the grey relations between criteria, which were measured according to the degree of similarity or difference in their development trend. In this way, a simple and relatively objective weighting process is achieved. However, the limitation of such methods is that the interdependence among criteria is not clearly specified, which is assumed to be exist before the calculation. Therefore, an objective incorporation process of interdependence among criteria under the premise to definitely identify the existence of interdependency might be an interesting topic for future research.

- Insufficient data collection process

Under the ideal situation, each stakeholder should give judgements on the direct weights and the interdependences in criteria respectively and combine them to indicate the composite weights. However, as explained in Section 3.3, the data collection for the interdependences in criteria was carried out by two decision-makers internally because of the complexity of BWM-DEMATEL. An average direct influence matrix was derived from these answers and combined with direct weights to calculate the composite weights. It is evident that the data collection process is simplified and cannot truly reflect the interrelationships in criteria. This might contribute to the small variations in criteria weights and rankings by incorporating the interdependency, which are presented in Chapter 4. To well collect data from stakeholders, a suggestion might be replacing the questionnaires by organizing workshops or interviews with stakeholders, to guide them to better understand the process and increase the efficiency.

Furthermore, it is worth noting that the decision-making process is limited in terms of both sample size and stakeholder diversity, consisting of only 8 researchers from various fields. This limitation may lead to the presence of extreme opinions and potential biases. To enhance the quality of the decision-making process, it is recommended to involve a broader range of stakeholders from different backgrounds.

- The impact of incorporating the interdependence among criteria on the ranking results

Chapter 4 presents the impact on the decision-making process of incorporating the interdependence among criteria. Overall, there are variations in criteria weights, but no variation in the final rankings. In this case study, the decision-making process is not sensitive to the variations in criteria weights, but more influenced by other factors (such as performance scores). Considering the complexity and cost of implementing the proposed method, it is questionable whether it is worth adopting this approach in this project. This question provides a potential new direction for future research. There is a need to develop an approach to estimate the impact of the interdependence among criteria on the alternatives ranking in a certain decision problem. In this way, the application value of BWM-DEMATEL in a specific decision problem can be evaluated, considering the cost of implementation in combination.

6. Conclusion

The development of ZLD desalination and the rising concerns about its sustainability call for a comprehensive sustainability assessment. A MCDM methodology consisting of BWM-DEMATEL, hierarchical clustering , and PROMETHEE is applied in this study, as part of the assessment to rank the sustainability performance of ZLD desalination scenarios with multiple objectives. Since desalination systems are characterized by intricate interactions among various factors which are seldom recognized in previous research, the research objective of this study is to explore the effects of interdependence among criteria on the MCDM process of sustainability assessment.

We developed a weighting method namely BWM-DEMATEL to quantify the interdependences among criteria and integrate them into criteria weights, and a desalination case study is used for demonstration. The results reveal that the integration of criteria interdependency in the MCDM process allows an analysis of cause-and-effect relationships, thereby facilitating the identification of factors crucial for the development of a sustainable desalination project. By incorporating the interdependency, there is a noticeable shift in the dispersion of stakeholder opinions on the criteria, attributed to an enhanced comprehension of the decision problem. However, the impact of interdependency on the final ranking is limited in cases which are not sensitive to the variation of criteria weights. In addition, although BWM-DEMATEL enables the integration of interdependence among criteria in the MCDM process, it is complex and time-consuming in terms of data collection. Since in some cases it may not yield different results compared to other simple weighting methods, it is important to carefully evaluate its applicability based on the specific context and trade-offs between complexity and potential benefits. Besides, in this case study, the implementation of hierarchical clustering effectively prevents the disregard of minority viewpoints during the aggregation of stakeholder opinions. Based on these, a robust ranking of desalination scenarios is produced through PROMETHEE.

One of the main limitations of this study is the insufficient data collection process. It is recommended to ensure a sufficiently large sample size when conducting surveys. Alternatively, organizing workshops or interviews with stakeholders might be more effective approaches for data collection. In future research, an approach can be developed to estimate the impact of the interdependence among criteria on the alternatives ranking in a certain decision problem, which is valuable for method selection in MCDM.

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Appendix

Appendix A

Analyses and requirements on the rest of characteristics of ranking methods in Table 3 are presented below:

- Simplicity

1) Description:

Simplicity refers to the intelligibility of the method and the simplicity of its structure. It determines the ease with which the method can be implemented, understood, and communicated to stakeholders. Simplicity depends on the complexity of the algorithm, the number of parameters introduced, etc.

2) Requirement:

The decision-making process should prioritize the quality of decision-making while also being comprehensible and comfortable for decision-makers and stakeholders.

3) Reason:

Given that sustainability assessments for desalination involve participation from various stakeholders and decision-makers, it is crucial to ensure that they are familiar with the evaluation process. The process should not be overly complex or difficult to understand, as this can create cognitive barriers and hinder participation. Thus, the evaluation process should be transparent, with a simple structure and as few parameters as possible.

- Type of problem solution

1) Description:

Current MCDM methods give mainly four types of problem solution to discrete multi-criteria problem (Munda 2008):

(α) Identifying one and only one final alternative.

(β) Assigning each alternative to an appropriate predefined category.

(γ) Ranking all feasible alternatives according to a total or partial preorder.

(δ) Describing relevant alternatives and their consequences.

2) Requirement:

A solution to the γ-problem is needed.

- Incommensurability

1) Description:

The idea of incommensurability refers to the difficulty of comparing and evaluating criteria that are inherently different in nature, and thus cannot be directly compared using a common metric or unit of measure. The two major processing ideas are to keep the decision criteria in their original units or to provide a better composition of the issue through normalization, which involves transforming the criteria into a common scale or unit of measure.

2) Requirement:

Retain the decision criteria in their original units throughout the decision-making process to enhance the transparency of the process.

- Comparability

1) Description:

Comparability refers to the possibility to perform an integrated comparison or to accept incomparable options in the final decision results. Some MCDM methods might produce incomparable alternatives in order to preserve the realistic features of alternatives, while other methods force generation of full rankings.

2) Requirement:

To achieve a precise determination of the position of the base scenario relative to the others, it is essential to ensure full comparability among them.

Appendix B

BWM questionnaire is adapted from a solver offered in https://bestworstmethod.com/. An example of BWM questionnaire is presented in Figure 18. The link for instruction video is: https://drive.google.com/file/d/1SYWI6534U9D4RUKrwNGF84h_-_bvIk1i/view?usp=sharing.

Criteria Number = 4	Dimension 1	Dimension 2	Dimension 3	Dimension 4
Names of dimensions	Technological	Economic	Environmental	Social

Select **the most important (best)** dimension with respect to **sustainability**	Environmental

Select **the least important (worst)** dimension with respect to **sustainability**	Technological

The meaning of the numbers 1-9:
1: **Equal** importance
2: Somewhat between Equal and Moderate
3: **Moderately** more important than
4: Somewhat between Moderate and Strong
5: **Strongly** more important than
6: Somewhat between Strong and Very strong
7: **Very strongly** important than
8: Somewhat between Very strong and Absolute
9: **Absolutly** more important than

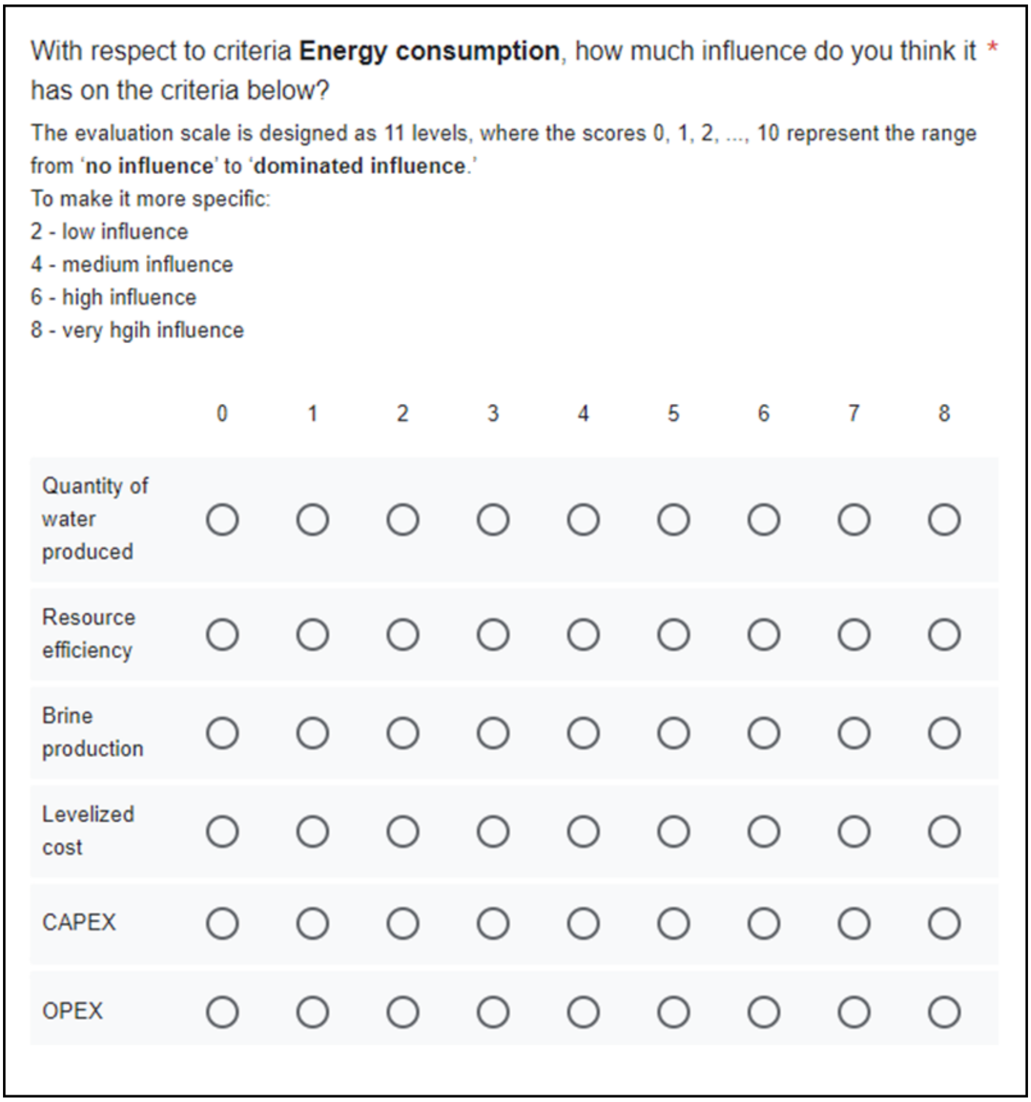
Best to Worst	Technological
Environmental	5

Best to Others	Technological	Economic	Environmental	Social
Environmental	5	3	1	2
Range		<=5		<=5

Others to the Worst	Technological	**Range**
Technological	1	
Economic	3	<=5
Environmental	5	
Social	4	<=5

Figure 18. A BWM questionnaire for evaluation of sustainability dimensions.

The link for DEMATEL questionnaire is: https://forms.gle/Ji1e9xMGaBwxE3Mj6. An example is presented in Figure 19.


With respect to criteria **Energy consumption**, how much influence do you think it has on the criteria below? *

The evaluation scale is designed as 11 levels, where the scores 0, 1, 2, ..., 10 represent the range from '**no influence**' to '**dominated influence**.'
To make it more specific:
2 - low influence
4 - medium influence
6 - high influence
8 - very hgih influence

	0	1	2	3	4	5	6	7	8
Quantity of water produced	○	○	○	○	○	○	○	○	○
Resource efficiency	○	○	○	○	○	○	○	○	○
Brine production	○	○	○	○	○	○	○	○	○
Levelized cost	○	○	○	○	○	○	○	○	○
CAPEX	○	○	○	○	○	○	○	○	○
OPEX	○	○	○	○	○	○	○	○	○

Figure 19. A DEMATEL questionnaire for evaluation of influences on criteria Energy consumption.

Appendix C

The selection of a preference function follows the procedure below:

1. If the criterion has a continuous numerical scale:

    a. If you want to introduce an indifference threshold (and thus neglect very small differences), consider using a Type V Linear preference function.

    b. If you want that even very small differences play some role in the PROMETHEE computation, consider using a Type III V-shape preference function.

2. If the criterion has a discrete numerical scale or a qualitative scale:

    a. If the number of possible values is small (<= 5) and if the values are perceived as quite different from each other, consider using a Type I Usual preference function.

    b. If the number of possible values is larger or if you want to have a weaker degree of preference for smaller differences, consider using a Type IV Level preference function.

In practice, the Type II preference function is seldom used. The Type VI preference function can be used as an alternative to the Type V preference function.

Appendix D

Table 10. Performance scores of desalination scenarios on each criterion.

Criteria	Unit	Scenario 1	Scenario 2	Scenario 3	Scenario 4
Energy consumption	Mwh/year	2,803.1	15,487.4	15,774.8	44,290.2
Quantity of water produced	m^3/year	123,424.3	106,697.5	134,998.2	51,323.6
Resource efficiency	(%)	96.2	89.9	88.5	25.0
Brine production	ton/year	-	-	-	-
Levelized cost	€/m^3	14.2	-354.0	-512.4	-9,932.0
CAPEX	€	29,461,907.4	44,504,879.5	36,991,991.6	27,560,168.3
OPEX	€/year	13,151.0	24,344.7	13,892.8	39,183.2
Production efficiency	%	0.2	13.0	30.1	89.3
Carbon dioxide emission	(ton CO_2-Equ)	5,550,064.4	30,665,134.5	31,234,028.7	87,694,651.5
Water footprint	m^3/year	-	233,013.2	217,995.3	706,826.9
Human toxicity	-	-	-	-	-
Operational complexity	-	3	2	2	2
Safe and healthy conditions	-	3	3	3	3
Local employment	-	4	3	3	3
Level of aesthetic acceptability	-	4	3	3	3

Note: the evaluation scale of social criteria: 1 – very bad; 2 – bad; 3 – average; 4 – good; 5 – very good.

Appendix E

The direct weights and composite weights from each stakeholder are presented in Table 11 and Table 12 respectively.

Table 11. Individual direct weights of criteria.

	Stakeholder 1	Stakeholder 2	Stakeholder 3	Stakeholder 4	Stakeholder 5	Stakeholder 6	Stakeholder 7	Stakeholder 8
Energy consumption	0.021	0.020	0.047	0.045	0.015	0.008	0.058	0.005
Quantity of water produced	0.012	0.020	0.088	0.013	0.027	0.024	0.058	0.008
Resource efficiency	0.012	0.036	0.027	0.006	0.050	0.005	0.070	0.008
Brine production	0.002	0.005	0.031	0.038	0.027	0.002	0.023	0.038
Levelized cost	0.075	0.110	0.020	0.015	0.055	0.051	0.041	0.130
CAPEX	0.010	0.010	0.003	0.015	0.027	0.017	0.071	0.039
OPEX	0.023	0.024	0.026	0.024	0.082	0.017	0.071	0.375
Production efficiency	0.023	0.036	0.020	0.010	0.136	0.017	0.132	0.087
Carbon dioxide emission	0.163	0.105	0.123	0.053	0.378	0.111	0.097	0.106
Water footprint	0.099	0.262	0.123	0.246	0.046	0.270	0.073	0.012
Human toxicity	0.065	0.105	0.123	0.229	0.086	0.029	0.146	0.023
Operational complexity	0.032	0.017	0.031	0.044	0.014	0.053	0.057	0.011
Safe and healthy conditions	0.262	0.065	0.154	0.168	0.036	0.292	0.057	0.096
Local employment	0.151	0.158	0.154	0.073	0.014	0.074	0.032	0.023
Level of aesthetic acceptability	0.051	0.028	0.031	0.023	0.006	0.031	0.013	0.039

Table 12. Individual composite weights of criteria.

	Stakeholder 1	Stakeholder 2	Stakeholder 3	Stakeholder 4	Stakeholder 5	Stakeholder 6	Stakeholder 7	Stakeholder 8
Energy consumption	0.023	0.023	0.048	0.046	0.018	0.011	0.058	0.008
Quantity of water produced	0.015	0.023	0.085	0.016	0.029	0.027	0.059	0.012
Resource efficiency	0.015	0.038	0.030	0.011	0.051	0.009	0.070	0.012
Brine production	0.005	0.009	0.033	0.039	0.029	0.006	0.026	0.039
Levelized cost	0.075	0.108	0.024	0.018	0.056	0.052	0.043	0.129
CAPEX	0.013	0.013	0.007	0.018	0.029	0.021	0.070	0.040
OPEX	0.029	0.030	0.031	0.028	0.082	0.022	0.073	0.357
Production efficiency	0.027	0.039	0.024	0.014	0.133	0.021	0.130	0.090
Carbon dioxide emission	0.156	0.101	0.118	0.052	0.356	0.107	0.094	0.102
Water footprint	0.095	0.247	0.117	0.232	0.046	0.254	0.071	0.013
Human toxicity	0.065	0.101	0.119	0.217	0.086	0.032	0.140	0.025
Operational complexity	0.035	0.020	0.033	0.045	0.017	0.055	0.057	0.014
Safe and healthy conditions	0.249	0.065	0.148	0.162	0.040	0.277	0.058	0.093
Local employment	0.146	0.153	0.149	0.074	0.018	0.074	0.035	0.027
Level of aesthetic acceptability	0.052	0.031	0.034	0.028	0.011	0.033	0.016	0.039

Appendix F

The direct and composite weights in cluster 2 are given in Table 13 and Figure 20. The alternatives rankings in cluster 2 according to direct weights and composite weights are given in Figure 21.

Table 13. Differences in direct and composite weights of dimensions in cluster 2.

	Direct weight (%)		Composite weight (%)		Relative variation (%)	
	Mean	S.D.	Mean	S.D.	Mean	S.D.
Technological	16.53	6.40	16.92	6.21	2.38	-2.96
Economic	30.79	1.12	30.81	1.07	0.07	-4.16
Environmental	41.29	13.73	39.63	12.92	-4.03	-5.95
Social	11.39	6.22	12.64	5.63	10.96	-9.35

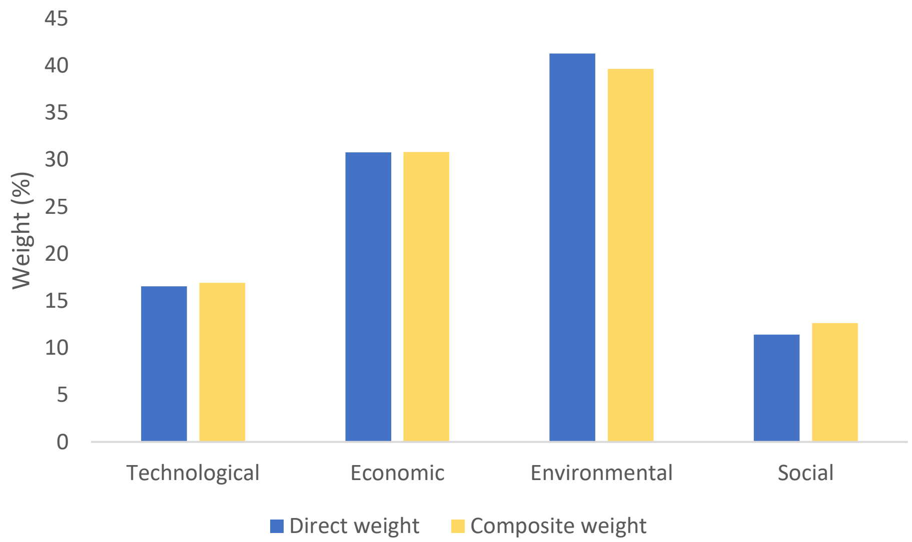


Figure 20. Direct and composite weights of dimensions in cluster 2.

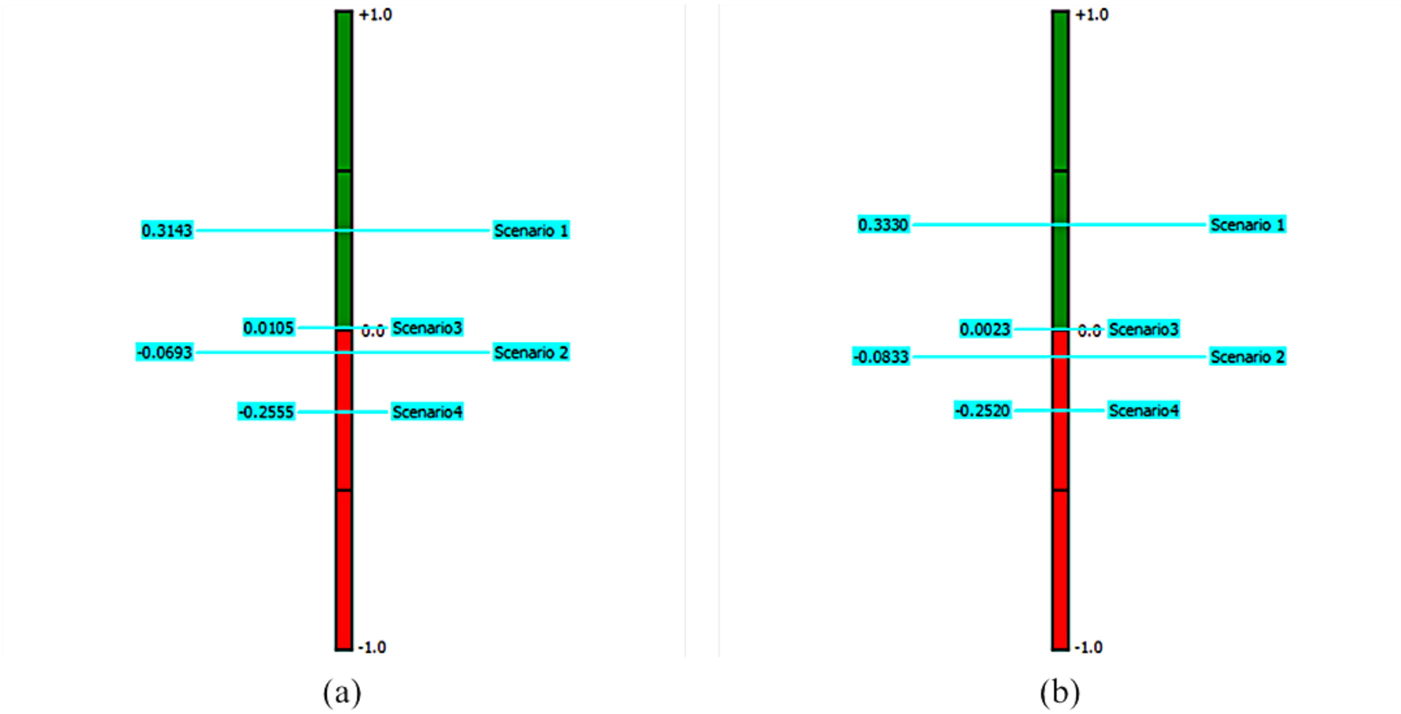


Figure 21. Alternatives rankings in cluster 2 according to direct weights and composite weights (From VISUAL PROMETHEE).

The direct and composite weights in cluster 3 are given in Table 14 and Figure 22. The alternatives rankings in cluster 3 according to direct weights and composite weights are given in Figure 23.

Table 14. Differences in direct and composite weights of dimensions in cluster 3.

	Direct weight (%)	Composite weight (%)	Relative variation (%)
Technological	16.53	16.92	2.38
Economic	30.79	30.81	0.07
Environmental	41.29	39.63	-4.03
Social	11.39	12.64	10.96

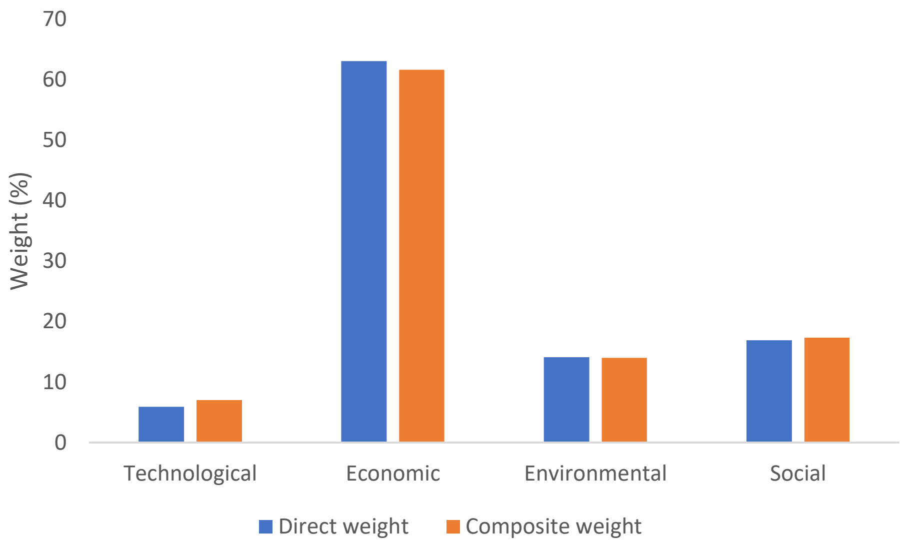


Figure 22. Direct and composite weights of dimensions in cluster 3.

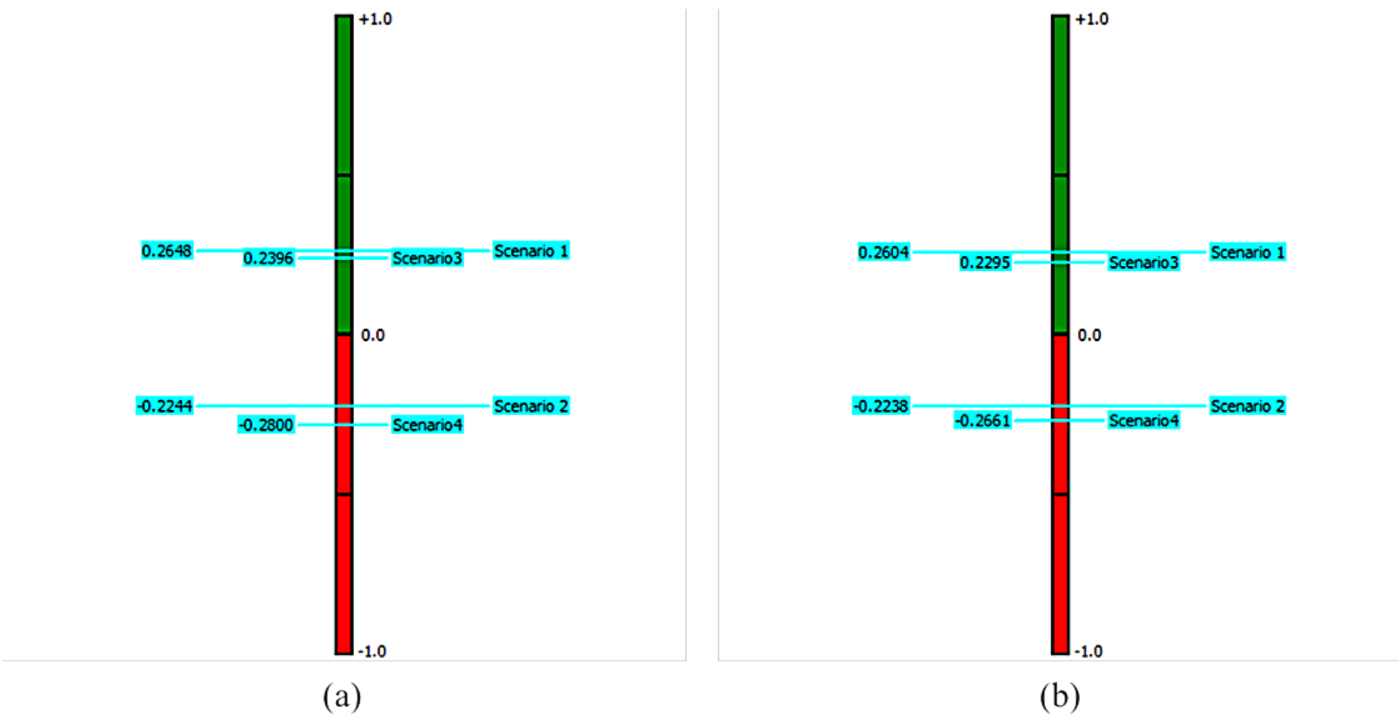


Figure 23. Alternatives rankings in cluster 3 according to direct weights and composite weights (From VISUAL PROMETHEE).

Appendix G

The strengths and weaknesses of desalination scenarios in each stakeholder cluster are presented in Figure 24, Figure 25, and Figure 26 respectively, where grey color represents technological dimension, blue color represents economic dimension, green color represents environmental dimension, and purple color represents social dimension.

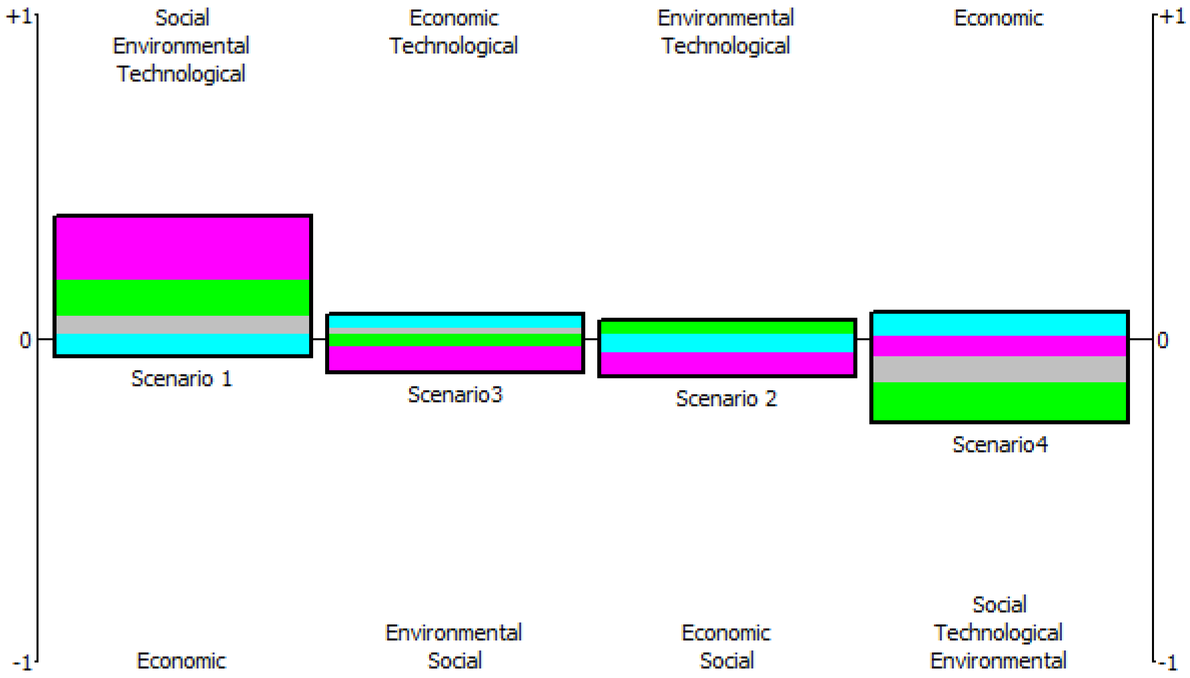


Figure 24. PROMETHEE Rainbow (dimension) in cluster 1 (From VISUAL PROMETHEE).

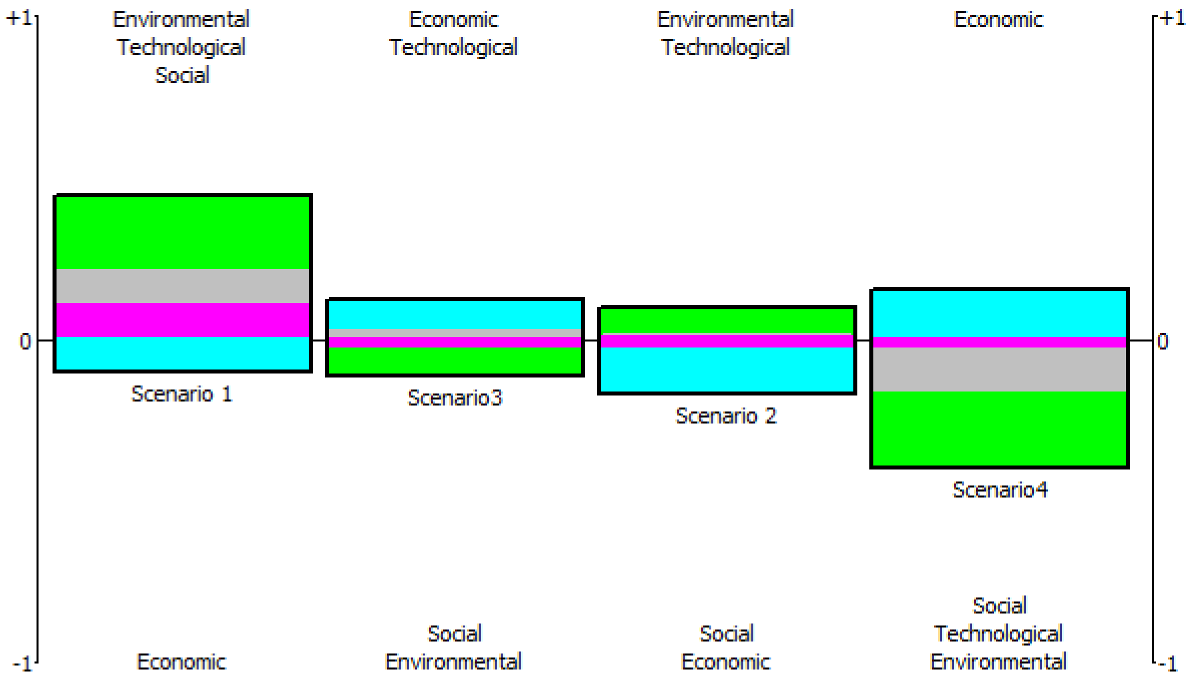


Figure 25. PROMETHEE Rainbow (dimension) in cluster 2 (From VISUAL PROMETHEE).

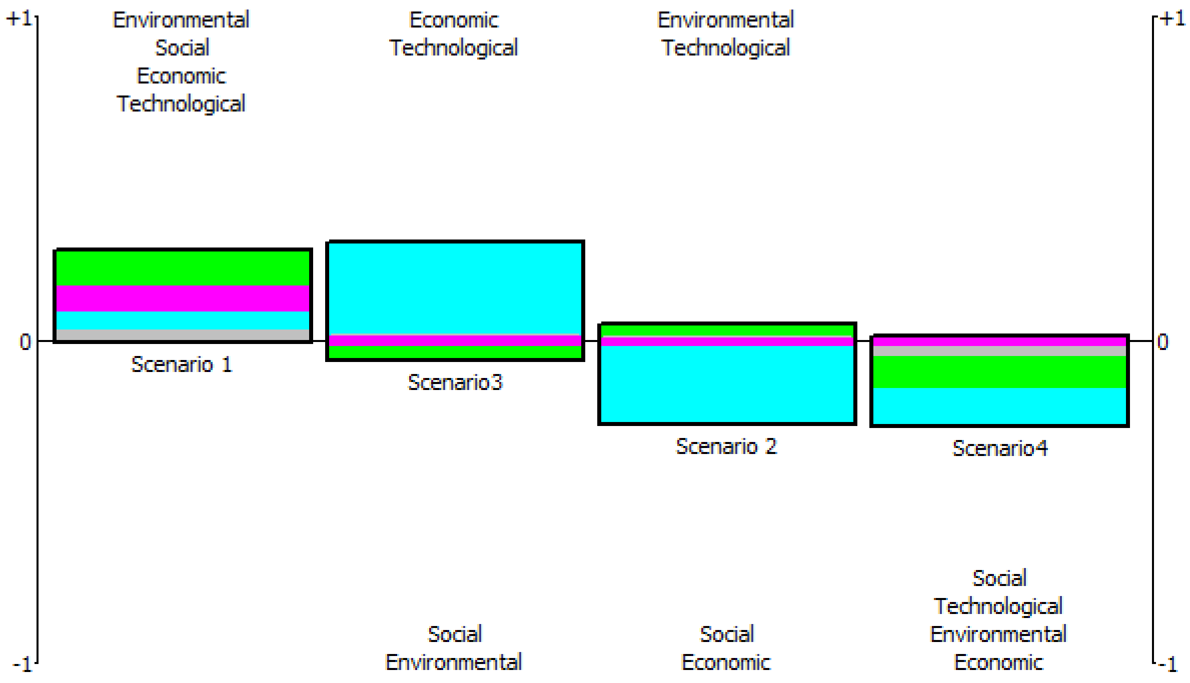


Figure 26. PROMETHEE Rainbow (dimension) in cluster 3 (From VISUAL PROMETHEE).