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Sustainability Ranking of Desalination Plants Using Mamdani Fuzzy Logic Inference Systems

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Abstract: As water desalination continues to expand globally, desalination plants are continually under pressure to meet the requirements of sustainable development. However, the majority of desalination sustainability research has focused on new desalination projects, with limited research on sustainability performance of existing desalination plants. This is particularly important while considering countries with limited resources for freshwater such as the United Arab Emirates (UAE) as it is heavily reliant on existing desalination infrastructure. In this regard, the current research deals with the sustainability analysis of desalination processes using a generic sustainability ranking framework based on Mamdani Fuzzy Logic Inference Systems. The fuzzy-based models were validated using data from two typical desalination plants in the UAE. The promising results obtained from the fuzzy ranking framework suggest this more in-depth sustainability analysis should be beneficial due to its flexibility and adaptability in meeting the requirements of desalination sustainability.

Keywords: artificial intelligence; decision-making in water supply; energy efficiency; ranking modelling framework; reverse osmosis; sustainability indicator list; sustainability tool; sustainable water production; unsustainable production; water pollution

1. Introduction

Desalination has rapidly expanded and evolved into a vitally important water source over many regions of the world. With this exponential regional growth of desalination comes significant economic, environmental and social impacts (or sustainability pillars) [1]. As a consequence, there is the increasing recognition by global, national, regional and institutional entities that the sustainability pillars should be applied to large physical and social development endeavours with desalination as being no exception [2].

Based on the report of the World Commission on Environment and Development, sustainability can be defined as "development that meets the needs of the present without compromising the ability of future generations to meet their own needs" [3]. From this report, wider sustainability definitions have been developed, which include the triple-bottom-line concept covering environmental, social and economic factors [4]. This approach considers each of the pillars of equal importance in the decision-making process [5–9]. In fact, up to seven sustainability pillars can be considered depending on the analysis and context in which the pillars are used [6,10].

Desalination is an energy-intensive process with various environmental, economic and social impacts. Therefore, desalination should be assessed according to its sustainability on these factors. However, the most commonly used sustainability framework generally focuses on one of the above-mentioned aspects [11]; for example, the well-established environmental life cycle analysis [12]. However, since the life cycle analysis does face limitations and model uncertainties [12,13], it ought to be integrated with a social-economic analysis for a better representation of sustainability [14]. Nevertheless, these types of integrated research are limited in the literature [11]. As an illustration, in research, the life cycle analysis was integrated with a water cost study focusing on a sea water reverse osmosis (SWRO) plant in Perth, Australia [15]. Nonetheless, this form of economic and environmental integration is more common than the integration of environmental and social analysis, as the corresponding evaluation tends to be more complicated and complex [11]. For example, Afgan et al. [16] considered four desalination options based on a Decision Support System Shell. However, there was no consideration as to the social factors and impacts of desalination. Therefore, desalination assessments may only incorporate a few economic parameters [15,17], or just provide a detailed cost–benefit analysis [18,19], all lacking the integration of all the three environmental, economic and social sustainability factors. Thus, it is recommended to apply an integrated sustainability assessment framework to consider all factors of desalination. This allows for the assessment of current or emerging desalination technologies for their relative sustainability [11]. Furthermore, Ibrahim et al. [11] suggested an integrated universal support framework incorporating several sustainability factors as subsets of four main sustainability components, including environmental, economic, social and technical factors.

A methodology for the evaluation of the sustainability pillars was proposed by Lior [2]; the method includes a relatively straightforward sustainability analysis of reverse osmosis (RO) desalination plants including a small number of calculation metrics. The methodology included equations for the formulation of a composite sustainability index in relation to relevant design and operational parameters. In this case, the methodology allows for a mathematical analysis including optimization and sensitivity evaluations. The method included the selection and calculation of metrics, in addition to weighting and aggregation, creating a sustainability indicator through sensitivity analysis between the choice of weights and the combined environmental and social impact factors [1].

For most regions, an environmental impact assessment is generally a legislative requirement prior to construction and operation of a proposed desalination plant. Fuentes-Bargues [20] presented an extensive environmental impact assessment on desalination works. Decision-makers tend to favour multi-criteria decision analysis methodologies such as variations of fuzzy logic applications and existing matrix mathematics, as these support research into the feasibility of new desalination projects. Common examples have been described [21–25]. Various indicators covered in these studies are based on economic, environmental/topographical, technological and social factors. Though, modifying existing operating plants to perform better in all facets of sustainability is imperative. Nonetheless, many desalination plants are still cutting costs to the detriment of environmental health, unless the practices are prohibited under reinforced and effective governmental water management legislation. Regional government agencies (e.g., the Ministry of Environment and Water in the UAE) can provide incentives for existing plants to adopt new sustainable practices due to research advancements. Additionally, regulatory bodies could encourage and adopt an effective ranking system to either buy water subsidies for founding a sustainable supply chain or publish information related to sustainable performance of works [26]. This will provide incentives to plant operators to enhance sustainable works' efficiency.

A ranking system such as the multi-criteria approach is a method that creates a list of sustainability indicators derived from a corresponding assessment. For example, Afgan and Darwish [16] ranked various desalination technologies with indicators in relation to economic influences, while considering fossil energy consumption to demonstrate the need of using this energy source sparingly. Chang [27] adopted an ecological indicator method to a seawater desalination bed to evaluate the impacts of this water production system within a vulnerable marine ecosystem. To improve the current practise of life-cycle assessments for environmental evaluation of desalination works, Zhou et al. [28] evaluated 30 desalination reports. They concluded that life-cycle assessments, in terms of their feasibility and reliability, contribute to the uncertainty in the evaluation outcome.

The selection of sustainability indicators as they relate to context is not considered to have a dynamic nature, i.e., an indicator framework is fixed, regardless of if the individual criterion fits the boundary conditions of plant operation. Therefore, it is essential to adopt a modelling framework that permits a certain degree of adjustment. This can close the gap between model developer and practitioner. This level of flexibility will be more appealing to decision-makers. Artificial intelligence (AI) techniques have been adopted to support the sustainability concept within technical issues. Among the several approaches to adopt AI techniques for system evaluation, artificial neural networks (ANN) and fuzzy logic (FL) systems have been prominently adopted in the area of sustainability [24,29]. For example, neural networks have been utilized by Abdeljawad et al. [30] to forecast key water parameters such as salt concentration to evaluate reverse osmosis plant performance along the Gaza Strip, Palestine. Additionally, an ANN has been used by Mashaly et al. [29] for assessing and optimizing solar performance under hyper arid environments. Furthermore, Kant and Sangwan [31] developed models utilizing ANN and support vector regression (SVR) methods to evaluate power consumption. During the model validation, it was found that the ANN yielded better results than the SVR model, emphasising the advantage of using ANN.

Gauging sustainability includes overcoming the barrier of being able to convert a holistic and intangible component to something that is quantifiable and tangible. Therefore, fuzzy logic is more predominant within multi-criteria decision-making tools as well as decision support systems that measure progress in terms of sustainability. Fuzzy logic supersedes these barriers by implementing the use of fuzzy set theory for the precise reason that this methodology is widespread among decision-makers for the development of models [32].

Gagliardi et al. [33] outlined a model to determine city sustainability with regard to urban planning, using a weighted fuzzy logic approach. Ghadimi et al. [34] also applied a comparable method to evaluate sustainability from start to finish. The benefit of these investigations was that expert knowledge is communicated within the evaluation framework, allowing for logical changes that the system may require to achieve enhanced performance in all aspects of sustainability. Ghassemi and Danesh [24] assessed the performance of desalination units compared to a set of indicators that was classified into environmental, technical and economical components using a hybrid-fuzzy multi-criteria decision analysis method. Reverse osmosis technologies were superior compared to multi-stage flash distillation plants, predominantly due to their compliance to renewable energy techniques.

As a ranking system necessitates evaluation by experienced practitioners in the sector for which the model is utilised, the techniques in the aforementioned research required quantification using sustainability performance figures, which are frequently problematic to attain. Fuzzy logic overcomes this barrier and permits linguistic evaluation, allowing contributions from various experts. To implement the desired ranking technique, methodologies should provide flexibility concerning the applied indicator set, recognizing the uncertainty in data and mimicking the human cognitive ability to allocate scores to the works under assessment. This is essential for a holistic sustainability assessment, with its associated wide-ranging influences.

Therefore, the aim of this study is to score the sustainable performance of desalination plants utilizing a fuzzy logic ranking framework based on a holistic indicator set that captures the performance of the plants. The current research features two UAE desalination plants as case studies. The modelling framework has been structured to exclusively score the performance of operational desalination plants.

2. Study Area and Case Studies

The Gulf Cooperation Council (GCC) countries and Yemen cover an area of approximately 2.8 million km^2 consisting primarily of arid and desert landscapes. On average, the precipitation is less than 100 mm/year in this region and, as a consequence, surface water sources are scarce [35]. This problem is exacerbated by the deep groundwater levels in the region (i.e., the amount of groundwater removal exceeding natural inflow), which makes the water scarcity values to be estimated at <500 m^3/capita/year [36]. Furthermore, water consumption in the region is one of the highest in the world [37], with an average water consumption rate of between 300 and 759 L per person per capita compared to the USA and China, with 580 L and 90 L per person per capita, respectively [38]. Additionally, water is highly subsidised in the Gulf region, with some consumers paying less than 5% of water production in some countries [39]. Consequently, significant backing has been given to the construction of desalination infrastructure to battle the increasing water demand in the Gulf region. For example, the UAE is currently one of the largest desalinated water-producing countries in the world, with a capacity at about 1776 million m^3/year, despite its relatively small landmass and population [40]. Seawater desalination remains one of the most reliable alternative sources of water in the Gulf region since its inception in the 1950s [41].

Desalinated water technologies continue to gain momentum in the Gulf region due to emerging technology and innovative research that allows for the development of more energy-efficient plants with lower operational costs. For example, research and development has reduced the excessive capital costs associated with plant construction, contributing to the reduction of the overall unit cost of desalinated water [42]. Nonetheless, the by-product of the desalination process is often criticized for its adverse environmental marine impacts in addition to its energy-intensive methods, both in terms of construction and operation [43].

The desalination industry in the Gulf is commanded by two important factors; namely, by the presence of already established plants, and the proposal of new desalination works projects. While there is considerable research and literature referencing the selection process of appropriate desalination technologies, under a certain set of boundary conditions or sustainability assessments of several desalination processes [44], there are few reports concerning the current operation of desalination plants. Therefore, it is important to consider and adopt a sustainable assessment methodology to assess and score the performance of existing desalination plants.

Desalination plants are assets requiring a considerable investment, which is recovered over a long timeframe. Therefore, the current scenario in the GCC foresees existing plants whose design was carried out based on now-obsolete energy, environmental requirements and the need for new plants. At the same time, the desalination technology is rapidly changing, with more energy-efficient and environmentally friendly processes being designed.

In this research, two generic and randomly selected anonymous UAE case studies have been utilized to demonstrate the model. Plant X adopted multi-stage flash distillation fuelled by natural gas from a cogeneration power plant and plant Y adopted reverse osmosis fuelled by natural gas obtained from a power plant.

3. Materials and Methods

3.1. Fuzzy Logic Systems

Mamdani and Assiliam [45] first introduced fuzzy logic models based on Zadeh's theory of fuzzy sets [46]. Fuzzy logic models have the capability to deal with highly uncertain systems [47].

Zadeh [46] introduced the theory of fuzzy sets by presenting a useful method of characterising the uncertainty and imprecision in data without the requirement of a challenging mathematical relationship. A distinct advantage to these models is the ability to present non-linear functions in a comprehendible linguistic style rather than presenting the information with numerical quantities. The models provide a convenient representation of human understanding in a legible manner applying fuzzy rules [47].

Fuzzy logic systems comprise four basic mechanisms, which are the fuzzification inference, knowledge base (also known as rule base or database), decision-making (called inference engine or inference mechanisms as well) and defuzzification [47,48]. The relation of these components is represented schematically in Figure 1, involving fuzzy logic operators, membership functions and fuzzy rules. The membership functions allow for the demonstration of a membership grade to a fuzzy set for a given number related to a linguistic label. Furthermore, the fuzzy 'if-then' rules present expert knowledge, which can be easily computed [47,48].

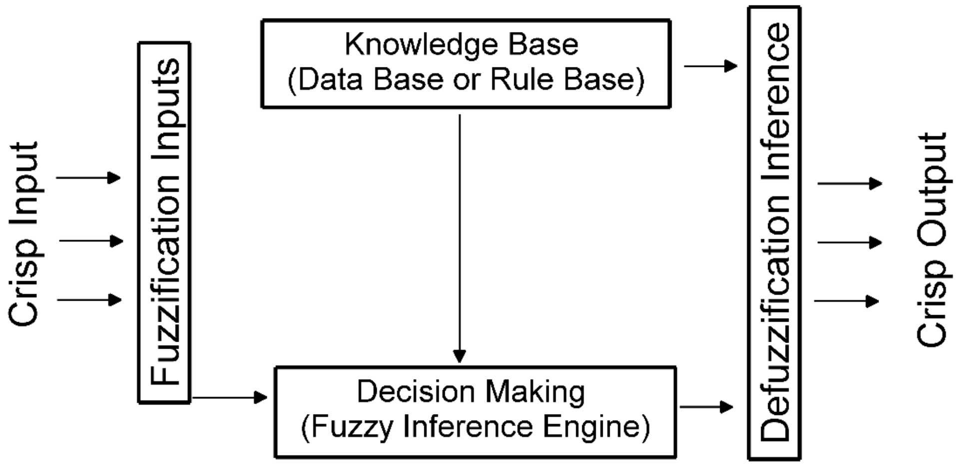

Figure 1. The basic structure of a fuzzy logic inference system and its components.

The goal of the fuzzification unit is to acquire the relationship degree of each input, whereby the data are processed and subsequently converted into linguistic variables with the help of relationship functions. The determiners of the relationship functions are linguistic expressions (e.g., weak, moderate and strong) where the outputs of this layer are a degree of fuzzy relationship of the inputs compromising of a value between zero and one [47,48].

The rule of fuzzy implication defines how several logic formulas comprising linguistic variables are related to each other. The amalgamation can be attained in various forms; however, it is derived from three essential procedures, which are the conjunction 'and', disjunction 'or' and negation 'not'. Furthermore, there is the implication (production rule) procedure. Additional information has been published elsewhere [47,48].

The fuzzy inference unit (alternatively, the decision-making or inference mechanism) applies a fuzzy reasoning procedure to obtain a fuzzy output. Thus, it combines the findings of the fuzzification process in a single fuzzy output for each instruction. Many fuzzy inference systems exist. However, a very frequently applied inference system is the Mamdani inference system (Figure 2) [47,48].

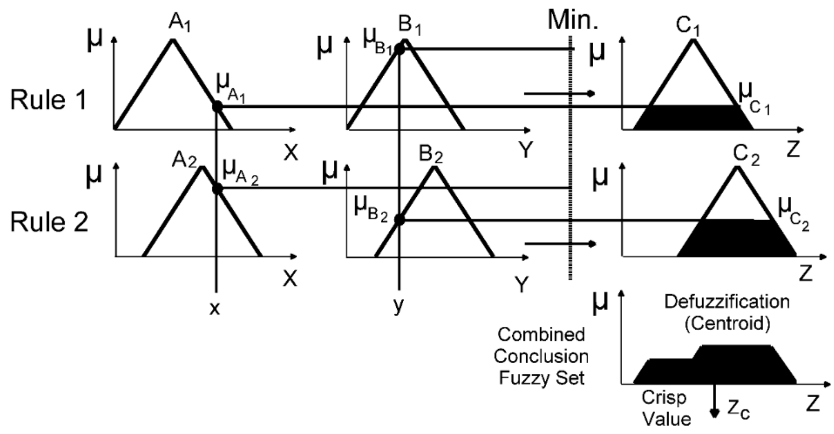

Figure 2. Schematic illustration of the Mamdani fuzzy inference system.

The defuzzification unit combines the output from all instructions that have been generated from a specific input and produces a crisp output. Thus, the fuzzy output is transformed back to a crisp number. The centre of gravity method is the most common means of defuzzification, whereby the gravity centre of the fuzzy set is quantified and projected onto the z-axis to obtain a crisp outcome. The result of this defuzzifier is the number z represented by Equation (1):

$$z = \frac{\int z_i \mu_{zi}(z_i) dz}{\int \mu_{zi}(z_i) dz} \tag{1}$$

where z is the crisp result and μ_{zi} represents the fuzzy membership number at z_i.

3.2. Sustainability Indicators

Examining similar themes within existing research provided selection criteria for indicators relevant to the aforementioned desalination operation challenges. A previous study reinforced the selected sub-criteria groups; namely, economic, environmental/topographical and social indicators. Specific researchers have utilized similar methodologies for their corresponding modelling approaches [16,21–23], though these investigations followed an exclusively quantitative method in obtaining their sets of indicators. Considering a more practical and operative resolution, decision-makers implementing water management guidelines commonly feel that it is easier to express needs in a linguistic manner rather than delivering quantitative information and particularly, data. Therefore, assuming a fuzzy logic method permits the system to take advantage from modelling the environment mimicking human cognitive conduct and allowing for linguistic input while recognizing the uncertainty of records.

The selection of key indicators in the current research focused on the Gulf region and more specifically on the UAE. This region has experienced an unprecedented rise of desalination plants with its ubiquitous operation, demanding a new framework to ensure sustainable operation while its market grows.

Sustainability metrics must satisfy some common-sense criteria while inclusive of the sustainability pillars, namely economic, environmental and social concerns [2]. This allows for relatively simple and widely understandable metrics, regardless of specific definitions and their complexity; thus, it makes it easier in terms of comparisons, replicability and satisfying the laws of nature [1,2]. In that regard, Figure 3 demonstrates the indicators designated for the current research. While evaluating the performance of the desalination plants against each indicator, the decision-maker is directed to comparatively appraise individual performance based on annual figures.

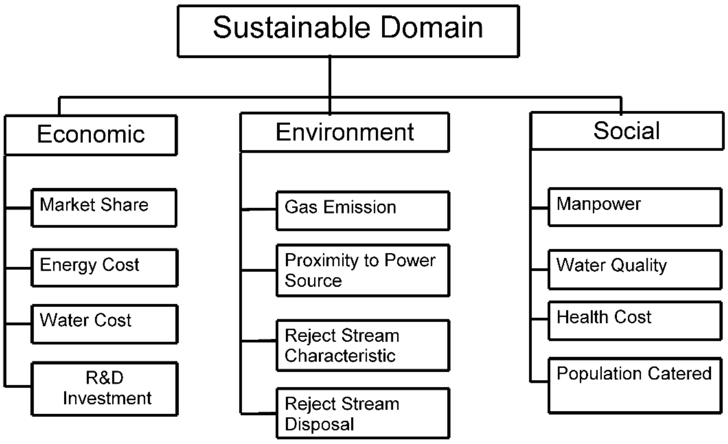

Figure 3. The selected sustainable indicator set including the economic, environmental and social factors used in this study.

3.2.1. Economic Criteria

Production expense of desalinated water will be contingent on the type of technology implemented, types of material utilized and the pricing of energy within the local area. Although thermal distillation procedures have reached their thermodynamic threshold, while maturing in terms of machinery, reverse osmosis processes have several operational factors that can be improved for greater performance. Development in this area has been limited to cost-reduction methods, resulting in increased adaptation of membrane practises [49].

The economic pillar of sustainability includes the overall cost of desalinated water (unsubsidized), inclusive of the cost of obtaining permits, potentially upwards of 60% of a major project cost [44]. Additionally, the economic pillar should include the cost and permitting of chemicals, including the impact of water on the local and national economy and land development. Furthermore, consideration should be given to an alternative water supply including the reduction of water demand through investment into efficient alternatives of water use.

Pricing strategies can encourage more efficient consumption. This can also lead to resource protection and pollution reduction. For example, in the European Union, once water subsidies were removed in some of the member states, water prices increased by 5- to 20-fold [2]. It is reported that most desalination plants have an associated cost of water production between \$0.45 and \$6.00 (USD) per m^3 [50], though many pricing projections are only related to the plant itself [51]. A more transparent method to cost estimation would be beneficial. However, existing cost estimations remain proprietary. Thus, exact estimates can be problematic, and, in turn, can make it difficult to develop tools for optimal plant configuration for comparison purposes [2]. The major sustainability economic criteria related to the desalination strategies are discussed below:

- Market share: The market share can be defined as the ratio of desalination capacity of the works to that of the nation [52]. For the purpose of this study, the market share solely relates to the UAE, which has been selected for illustration purposes of the generic model.
- Energy costs: Desalination works operate on energy produced by power units; either thermal or mechanical energy with distillation and reverse osmosis plants in this order. Reverse osmosis plants require mechanical energy, which can be seen as more flexible in regard to waste heat (cogeneration configuration) and/or a renewable energy options such as solar. Holistic energy pricing factors have been discussed in other resources [53].
- Water costs: The unit cost of water (usually per m^3) is an amalgamation of the capital, operational, maintenance, fuel and other financial costs [44,54]. This unit cost is estimated by taking the total yearly cost of manufacture and dividing it by the total annual volume.

- Research and development investment: Numerous companies that operate desalination works create research and development departments (or similar entities) to discover potential areas to elevate their competitiveness. These departments have often demonstrated a valuable return on investment for their respective companies.

3.2.2. Environmental Criteria

Previous research on the environmental impact of desalination and related ancillary components suggest the energy component of desalination is one of the most important contributors to environmental impact, including climate change, due to the fossil fuels typically driving the plants [50,55]. Energy is indeed an important contributor, however, research into plants using renewable energies demonstrate much lower environmental impact [56–58]. Therefore, all environmental impacts should be considered from all of the other desalination environmental pressures.

The public is often concerned about the environmental impact that the brine discharge produced by the desalination process brings to the ocean and the marine life. Thermal desalination presents a higher environmental footprint as all the low grade energy received from the power plant and used for the distillation process is also discharged into the sea [59].

The environmental pillar should strive to include feed water effects, environmental impacts on the existing freshwater resources, energy supply emissions and the effect on current water consuming sectors including agriculture [2]. All aspects of desalination procedures, from the water intake system to the reject stream disposal, create potential adverse effects to the surrounding ecosystem.

Environmental impacts associated with desalination plants can be grouped based on the source of impact [27]. For example, the operation of the intake structure will primarily lead to an uprooting of the seabed, whereas, during post construction, marine organisms are at risk of injury or could be killed due to the strong intake current. Additionally, the installation of these structures can interfere with human, commercial and recreational activities alike [60].

Furthermore, the introduction of desalination chemical by-products into the environment can be detrimental for the long-term, especially while considering their characteristic toxic constituents. Nonetheless, biological fouling is observed in the majority of desalination plants. Chlorine is a chemical utilised to limit the biological fouling potential. It can be added to the intake feed water, preventing fouling through subsequent stages of the desalination processes [61].

Additionally, phosphonates and polycarbonic acids are utilized as inhibitors to scale formation within pipelines that are carrying feed water. Although these chemicals are considered benign to marine organisms, corresponding low degradation rates can lead to persistence and accumulation in the discharged environment with low rates of decomposition, which result in their persistance in the receiving environment, eventually resulting in eutrophication at the disposal site [27].

In reverse osmosis plants, coagulants are common as they are utilized with the application of membrane technology. Thus, they can play an essential role in the effectiveness of reverse osmosis practise. Though harmless in nature, ferric chloride and other by-products can lead to increased turbidity near the ocean surface that can adversely impact on the photosynthesis process that is vital for organism survival [61]. Polyethylene, polypropylene glycols and other antifoaming agents can be applied to avert foaming in thermal desalination works. Though harmless, there can be a bioaccumulation risk [43].

Lastly, atmospheric pollution can be explained by the operation of a desalination plant, though this depends predominantly on the quality of the fuel used. Typical emission gases such as carbon, sulphur and nitrogen oxides are commonly estimated per unit of desalted produced water [62]. Several main environmental factors that impact on desalination projects are described below:

- Gas emissions: Distillation works release atmospheric contaminants consisting typically of carbon dioxide, sulphur dioxide and several nitrogen oxide gases during the energy production phase of operation. Additionally, reverse osmosis membrane processes may also release such gases throughout operation. Hence, this drawback should also be considered while using this indicator to measure system performance [62]. Thermal desalination plants are associated with large power generation plant and extract low-pressure steam [63], which is either extracted from a condensing or backpressure steam turbine.

- Proximity to a power source: Previous field development has acknowledged that a cogeneration power desalting plant requires less fuel energy in direct comparison to a single-purpose desalting unit. Single source thermal desalination is no longer highly thermodynamically unsustainable. There is a momentum in the industry towards decoupling water and power. Reverse osmosis technology prevails.
- Reject stream characteristics: Salinity, temperature and biocide concentration are all by-products of the reject process [64]. Therefore, there needs to be a holistic appraisal of the reject stream quality based on yearly numbers, so one can evaluate the plant's contribution to environmental well-being.
- Reject stream dumping: The dumping of brine and other chemical effluent from a plant should take this into consideration, while adopting more sustainable disposal techniques [64].

3.2.3. Social Criteria

The society pillar includes impacts on health, land use and development, and employment (including employment safety) [2]. New desalination projects, especially larger ones, can have a profound impact on social structures in the community where they are located. Nonetheless, social pillars due to existing desalination also include health, land use and employment.

Typically, a higher standard of living will correlate to increased water consumption, which can—especially in the case of the UAE—create a major strain on the already dwindling water resources. Inevitably, a major dependence on desalination plants is created in water-scarce regions. Water scarcity can be far-reaching, from geographical to water demand factors. However, quantification of these aspects can be undertaken by determining the population base served by each desalination plant, while taking into account various case-specific municipality factors. Therefore, societal factors can be evaluated by the satisfaction of the stakeholders involved, both at the operation and consumer level [25]. Generally, governments promote master planning that forecasts the water demand as a result of population increase, industrial demand, tourism, agricultural development and development of living standards. Related social criteria are discussed below:

- Labour force: The plants require a certain level of administration, security, purchasing of spare parts, routine maintenance and general overhauls.
- Water quality: Water quality is highly regulated through the development of international standards such as the World Health Organization (WHO).
- Health costs: The construction of a desalination plant is subject to an environmental approval whereby the discharge flow from the plant may not exceed the levels stated by the statutory requirements. Health costs for a desalination plant are determined through the health and safety procedures of the desalination plants.
- Population: The objectives of desalting water can vary depending on the end-users' specific desires for the purified water. The water demand has significantly increased in recent years, especially in cities such as Dubai and Abu Dhabi, which has strained the existing groundwater resources.
- Technology: Various desalination techniques and methodologies, such as multi-stage flash thermal distillation works and reverse osmosis desalting works utilize energy in varying forms, while differing in the amount of energy consumption for each one.

4. Application

4.1. Modelling Framework

To develop a practical and quick modelling framework, decision-makers or authoritative representatives would have to rate the aforementioned indicators, serving as the inputs for the proposed ranking modelling system based on delegated scores. Next, the decision-maker's ratings would be entered into individual fuzzy systems that would provide output scores. However, it would be advantageous to integrate fuzzy systems into a ranking framework, thereby easing the handling of data in relation to scores within individual domains, sub-domains, etc.

The ranking model framework is generalized in Figure 4, highlighting the division of three stages to differentiate between the types of fuzzy models defined. However, the rule base compilation would be far more difficult, if the design model accounted for two or more inputs. Nonetheless, fuzzy logic does possess an advantage through its flexibility and number of indicators and domains. Therefore, decision-makers are unrestrained in regard to adding or deleting indicators, if the purpose is to enhance the quality of the final score. Alterations would lead to a variation of the model numbers applied during the initial stage.

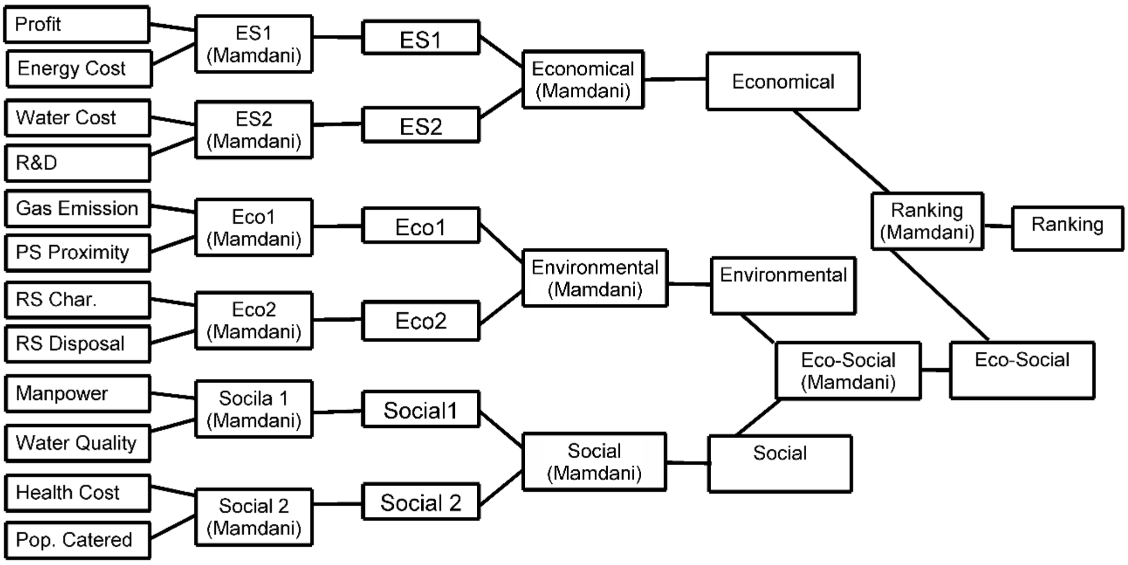

Figure 4. Schematic of the fuzzy inference modelling framework.

The left-hand part of Figure 4 highlights the implementation of the first phase models grouping the twelve indicators under a specific area. The models of this stage output the performance scores of the works under each domain. The second stage function aims to appraise and consolidate presentation scores of each area into two variables acting as inputs to the last ranking model. The classification of indicators into domains determines the number of models in the second stage. The third phase comprises of one fuzzy model, whereby the output provides the last ranking mark (Figure 4). Therefore, the scores of specific desalination plants can be utilized as a sustainable performance ranking system between each plant by water authorities or the decision-makers according to relevant scenarios.

4.2. Proposed Ranking Model

Data received from the research literature (see below) provide the foundation for the proposed ranking method. The findings of running the model are displayed and the methodology is validated to test its effectiveness.

The ranking model comprises the Mamdani inference system, and was designed using MATLAB computing language, applying the fuzzy logic toolbox with a set of indicators providing the inputs to the fuzzy inference model. The membership function is utilized to allocate the ranking values that are designated to the inputs. The fuzzy inference model framework consists of three stages covering all aspects of plant performance, while bringing the performance range from the input (1–10) to the output (1–100) for a complete but crisp output score.

The membership functions for the inputs of the initial phase split the range (1–10) into four fuzzy sets with differing linguistic variables; namely, weak performance (WP), moderate performance

(MP), strong performance (SP) and excellent performance (EP). Figure 5 schematically represents the membership functions of the input and output of the first stage.

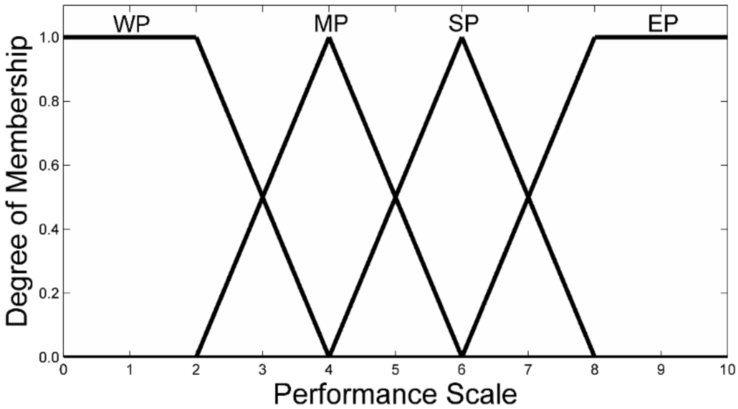

Figure 5. Membership function defined for the inputs of stages 1 and 2 as well as the output of stage 1 (profit, energy cost, water cost, research and development, gas emission, RS characteristics, RS disposal, manpower, water quality, health care, population catered for, ES1, ES2, Eco1, Eco2, Social 1 and Social 2). WP, weak performance; MP, moderate performance; SP, strong performance; and EP, excellent performance.

The input membership functions of the second phase follow a comparable grouping to the input and output membership functions from the first one. The number of membership functions in the output is increased from two to six. The membership functions for the second stage output are as follows: weak performance (WP), low–moderate performance (LMP), high–moderate performance (HMP), strong performance (SP), very strong performance (VSP) and excellent performance (EP), as highlighted in Figure 6.

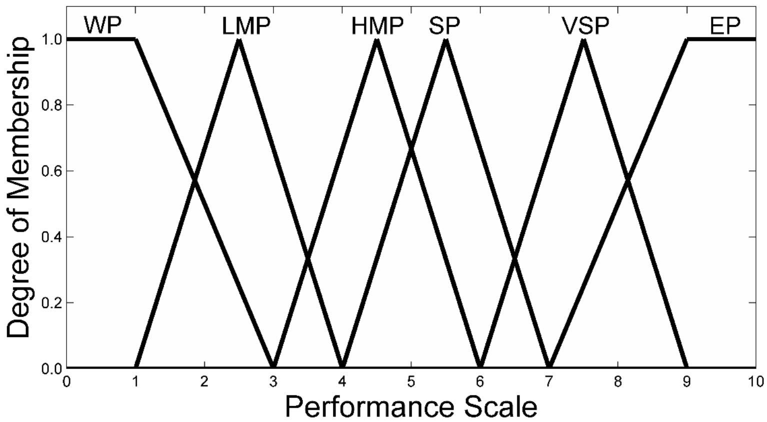

Figure 6. Membership function defined for inputs of stages 2 and 3 as well as output of stage 2 (economical, environmental, social and eco-social). WP, weak performance; LMP, low–moderate performance; HMP, high–moderate performance; SP, strong performance; VSP, very strong performance; and EP, excellent performance.

The membership function input mechanism in the third stage replicates the findings of the second stage; i.e., the six fuzzy sets of the membership function described, previously. The final phase is an integration of the three areas and offers the last crisp score for the plant under appraisal, consequently, the output range is 1–100. The quantity of membership functions needed to encapsulate all options of plant performance increases by one to seven, which has been presented in Figure 7, with the seven linguistic variables tagged as very weak performance (VWP), weak performance (WP), low–moderate performance (LMP), high–moderate performance (HMP), strong performance (SP), very strong performance (VSP) and excellent performance (EP).

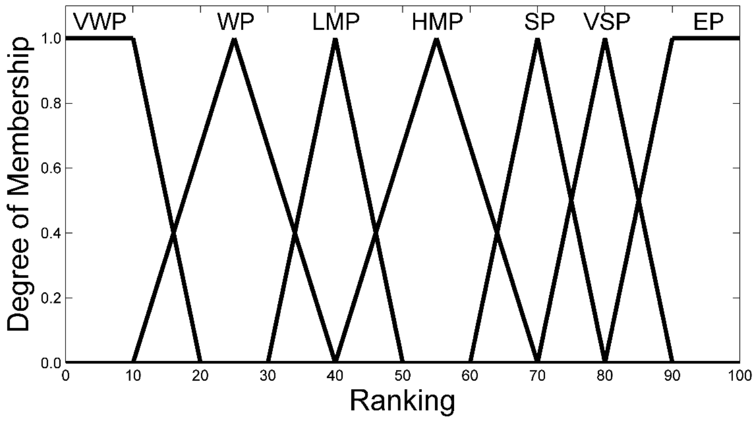

Figure 7. Membership function defined for the output of stage 3.

The knowledge base is comprised of a database and a rule base, where the ranking method uses the in-built classification of the trapezoidal and triangular functions, in addition to the fuzzy operator 'and' to manage the rule base. The rule base is established through expert understanding from research and supports the model to deliver the crisp numbers. The rules outlined at each phase are contingent on the nature of input information as well as the input and output membership function arrangements. Therefore, the rules vary for each phase. The rule base is presented in Tables 1–3.

For the defuzzification unit, the Mamdani inference system utilizes schematic approaches to adapt the fuzzy numbers, providing a crisp output. During defuzzification, the centroid of area method is utilized, and is shown by Equation (2):

$$F\,(x_i) = \frac{\sum_i x_i \times \mu_{\overline{A}}(x_i)}{\sum_i \mu_{\overline{A}}(x_i)} \tag{2}$$

Table 1. Rule base for stage 1 (Models ES1, ES2, Eco1, Eco2, Social 1 and Social 2).

Rule Number	if Input 1 Is	and	Input 2 Is	Then	Output 1 Is
1	WP		WP		WP
2	WP		MP		WP
3	WP		SP		MP
4	WP		EP		MP
5	MP		WP		WP
6	MP		MP		WP
7	MP		SP		MP
8	MP		EP		SP
9	SP		WP		MP
10	SP		MP		MP
11	SP		SP		SP
12	SP		EP		SP
13	EP		WP		MP
14	EP		MP		SP
15	EP		SP		SP
16	EP		EP		EP

VWP, very weak performance; WP, weak performance; LMP, low–moderate performance; HMP, high–moderate performance; SP, strong performance; VSP, very strong performance; and EP, excellent performance.

Table 2. Rule base for stage 2 (Economical, Environmental and Social).

Rule Number	if Input 1 Is	and	Input 2 Is	Then	Output 1 Is
1	WP		WP		WP
2	WP		MP		WP
3	WP		SP		LMP
4	WP		EP		HMP
5	MP		WP		WP
6	MP		MP		LMP
7	MP		SP		HMP
8	MP		EP		SP
9	SP		WP		LMP
10	SP		MP		HMP
11	SP		SP		SP
12	SP		EP		VSP
13	EP		WP		HMP
14	EP		MP		SP
15	EP		SP		VSP
16	EP		EP		EP

VWP, very weak performance; WP, weak performance; LMP, low–moderate performance; HMP, high–moderate performance; SP, strong performance; VSP, very strong performance; and EP, excellent performance.

Table 3. Rule base for stage 3 (Eco-Social and Ranking).

Rule Number	if Input 1 Is	and	Input 2 Is	Then	Output 1 Is
1	WP		WP		WP
2	WP		LMP		WP
3	WP		HMP		LMP
4	WP		SP		LMP
5	WP		VSP		HMP
6	WP		EP		SP
7	LMP		WP		WP
8	LMP		LMP		LMP
9	LMP		HMP		HMP
10	LMP		SP		HMP
11	LMP		VSP		HMP
12	LMP		EP		SP
13	HMP		WP		LMP
14	HMP		LMP		LMP
15	HMP		HMP		HMP
16	HMP		SP		HMP
17	HMP		VSP		SP
18	HMP		EP		SP
19	SP		WP		LMP
20	SP		LMP		HMP
21	SP		HMP		SP
22	SP		SP		SP
23	SP		VSP		SP
24	SP		EP		VSP
25	VSP		WP		HMP
26	VSP		LMP		HMP
27	VSP		HMP		SP
28	VSP		SP		SP
29	VSP		VSP		VSP
30	VSP		EP		VSP
31	EP		WP		SP
32	EP		LMP		SP
33	EP		HMP		VSP
34	EP		SP		VSP
35	EP		VSP		VSP
36	EP		EP		EP

VWP, very weak performance; WP, weak performance; LMP, low–moderate performance; HMP, high–moderate performance; SP, strong performance; VSP, very strong performance; and EP, excellent performance.

5. Results

As mentioned earlier, this study takes into account two generic case studies in the UAE to demonstrate the fuzzy model. Corresponding specifications and performance indicators from two these desalination plants with differing technologies are highlighted in Tables 4 and 5. The inputs for the model were selected and provided by desalination plant decision-makers. To guarantee participants' mindfulness of their part in the research, a brief summary on the subject and the modelling framework was sent to participants working in the field. From here, the participants were requested to rate the production of the desalination plant with reflection of the specific indicators. Table 6 provides the averages of the participants' responses for the sample plant data provided.

Table 4. Operational specifications for plant X.

Component	Specification
Technology adopted	Multi-stage flash distillation fuelled by natural gas from cogeneration power plant
Million Imperial gallons per day	35 [65]
Market share	In context of the United Arabic Emirates market, Plant X produces 1.9% [66]
Energy cost	0.085 $/kWh [23]
Water cost	0.586 $\$/m^3$ [23]
Research and development investment	The corporation has a department dedicated to research and development, but no new findings have been reported.
Gas emissions	Totalling to 16,450 $\times 10^6$ kg between 2010 and 2015 [23]
Reject stream	Salinity, temperature and biocide concentration are 50,000 mg/L, 5 to 15 °C above ambient and 2 mg/L, respectively. Disposed-off into the ocean without treatment via submerged pipes located far out in the ocean [5].
Manpower	7.35 $\times 10^3$ people [23]
Water quality	Total dissolved solids amount to 10 ppm after desalination [22]
Health costs	Due to NO_X gases, 2.24 $\times 10^9$ $ [23]
Population catered for	The number of consumers totalled 51,405 people [65]

Table 5. Operational specifications for plant Y.

Component	Specification
Technology adopted	Reverse osmosis fuelled by natural gas obtained from a power plant 2 km away.
Million Imperial gallons per day	In context of the United Arabic Emirates market, Plant Y produces 1.36% [66]
Market share	25 [66]
Energy cost	0.085 $/kWh [23]
Water cost	0.535 $\$/m^3$ [23]
Research and development investment	The corporation operating the plant has invested resources to check the feasibility of a chip that uses electricity to separate salt from water. The new breakthrough can potentially negate the usage of chemicals for pre-treatment in the reverse osmosis process.
Gas emissions	Totalling to 12,236 $\times 10^6$ kg between 2010 and 2015 [23]
Reject stream	Salinity, temperature and biocide concentrations are 65,000–85,000 mg/L, ambient and negligible, respectively. Disposed-off into the ocean without treatment [67].
Manpower	4.45 $\times 10^3$ people [23]
Water quality	Total dissolved oxygen amounts to 35–500 ppm after desalination [22].
Health costs	Due to NO_X gases, 2 $\times 10^9$ $ [23]
Population catered for	The number of consumers totalled 36,371 people [65]

Table 6. Sample data collected for performance rating (out of 10, where 10 indicates the best performance) of desalination plants.

Criteria		Sub-criteria	Plant X	Plant Y
Economical	1	Market share	6	4
	2	Energy cost	8	8
	3	Water cost	6	8
	4	Research and development investment	5	8
Environ-mental	5	Gas emissions	3	5
	6	Power source proximity	9	5
	7	Reject stream characteristics	6	7
	8	Reject stream disposal	5	8
Social	9	Manpower	7	6
	10	Water quality	9	5
	11	Health costs	3	5
	12	Population catered for	7	5

Tables 7 and 8 provide the ranking performance of the fuzzy model for the two case studies. Figures 8 and 9 present the surface views of all eleven models utilized in the framework. Running the fuzzy inference system model 'ranking' results in the final sustainable performance scores. Concerning the example desalination works, about 61% for plant X and 70% for plant Y were obtained.

Table 7. Ranking output for case X.

Criteria		Sub-criteria	Plant X	Stage 1 Output	Stage 2 Output		Stage 3 Output
Economical	1	Market share	6	ES1=6	Economical=5		
	2	Energy cost	8				
	3	Water cost	6	ES2=5			
	4	Research and development investment	5				
Environmental	5	Gas emissions	3	Eco1=5	Environmental=5		Ranking=60.62%
	6	Power source proximity	9				
	7	Reject stream characteristics	6	Eco2=5			
	8	Reject stream disposal	5				
Social	9	Manpower	7	Social 1=7.27	Social=6.13	Eco-Social=5	
	10	Water quality	9				
	11	Health costs	3	Social 2=5			
	12	Population catered for	7				

Table 8. Ranking output for case B.

Criteria		Sub-Criteria	Plant Y	Stage 1 Output	Stage 2 Output		Stage 3 Output
Economical	1	Market share	4	ES1=5.5	Economical=6.89		
	2	Energy cost	8				
	3	Water cost	8	ES2=8.47			
	4	Research and development investment	8				
Environmental	5	Gas emissions	5	Eco1=5	Environmental=6.13		Ranking=70%
	6	Power source proximity	5				
	7	Reject stream characteristics	7	Eco2=7.27			
	8	Reject stream disposal	8				
Social	9	Manpower	6	Social 1=5	Social=5	Eco-Social=5.5	
	10	Water quality	5				
	11	Health costs	5	Social 2=5			
	12	Population catered for	5				

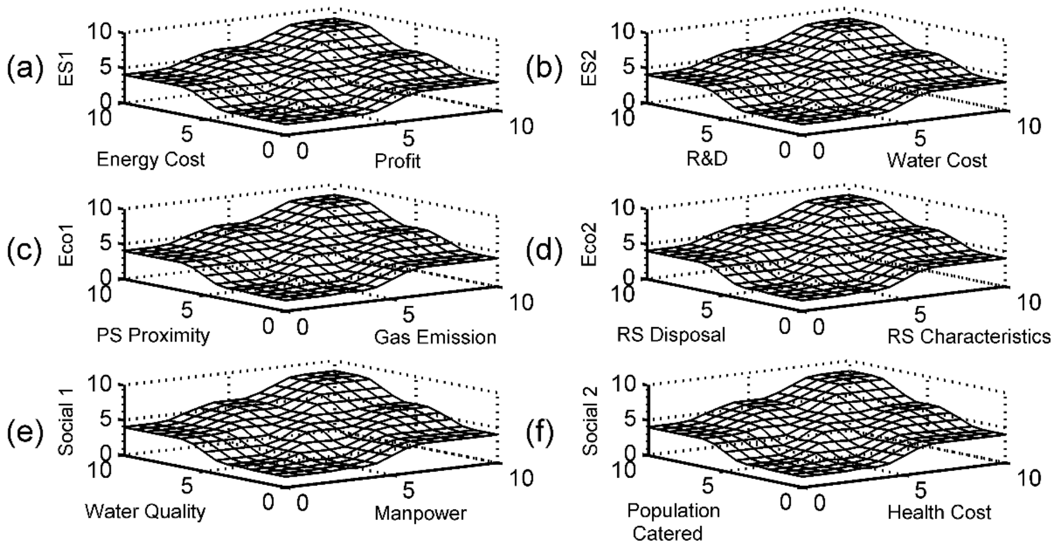

Figure 8. Surface views of stage 1 models.

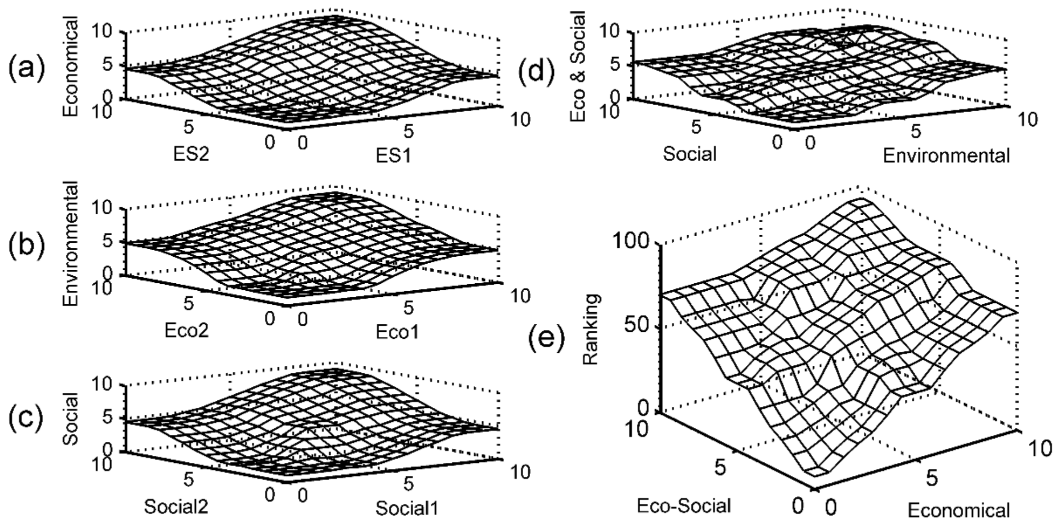

Figure 9. Surface views of stages 2 and 3 models.

6. Discussion

This section aims to discuss the potential of using fuzzy logic in sustainability assessment based on the results of the present study and related published work. In the last decade, several researchers attempted to employ fuzzy logic for this purpose. In a study conducted by Phillis and Andriantiatsaholiniaina [68], fuzzy logic operations were represented as powerful tools for compensating the lack of full knowledge in existing methods of sustainability measurement.

Other related studies emphasized the necessity of applying fuzzy propositions as capable alternatives for evaluating strong sustainability of ecosystems [69,70], ecology [71], and environmental systems [72]. The use of fuzzy logic in assessment of industrial sustainability, which is a very challenging task, has also been reported in the literature [73,74]. Moreover, in light of the current topic of this paper, several publications have studied the fuzzy-based approaches for evaluating sustainability in various areas of hydraulics and hydrosiences such as soil-water interaction [75], self-purifying capacity of rivers [76] and groundwater [77]. The findings of the study show that the fuzzy-based models can considerably help decision-makers in their assessment of the intended problem.

In the current study, we proposed a methodology for sustainability ranking of desalination plants using the Mamdani Fuzzy Logic Inference Systems. In the developed model, the various rule bases used for the individual fuzzy inference system model adopt the linguistic individual score, integrates it and subsequently transforms it to a more adequate form of holistic quantified information utilized for ranking. If the input values for 'economic', 'environment' and 'society' increase, the corresponding output 'ranking' also rises, as seen in Figure 8. Furthermore, depending on the preference of the user, the proposed model can easily be made more complex by adding weights to the selected criteria depending on the specific case study context.

Several studies [16,24] indicate superior sustainability performance of reverse osmosis processes over multi-stage flash distillation. However, it should be taken into consideration that the corresponding research is based on a designed framework to adopt the most appropriate desalination units for a specific context. In contrast, the current research proposed a model software structure to judge the sustainability performance of current desalination plants.

The validation of the findings overcome the barriers to accomplish sustainability in desalination works. In the perspective of the UAE case study country, the outcomes promote a required step change of the desalination market by promoting additional membrane separation techniques, which currently constitute, for example, only 12% of the desalination plants in the UAE.

The methodology described in this study can provide decision-makers with a tool to derive information from dissimilar databases. The fuzzy ranking framework amalgamates various expert knowledge to yield a single indicator used for sustainability ranking for easy evaluation between the proposed planning scenarios.

As a result, the decision-makers can find areas to be improved by investments to promote the sustainability of the desalination plant. The surface views of the model provide an easy tool to understand how the single ranking was derived.

The proposed model was validated using data available in the literature for the UAE. However, validating the model with real data would enrich the outcome. To demonstrate the superiority of this approach, the proposed methodology should be repeated for other regions to take into consideration other local factors as it is expected that sustainability values given by experts vary for other countries and hence may change the overall sustainability rank.

7. Conclusions and Recommendations

This paper describes a new fuzzy logic framework applied to the sustainability ranking for desalination plants in the UAE. It includes the most widely used sustainability indicators that were aggregated using the Mamdani fuzzy framework. These indicators cover the economic, social and environmental sustainability pillars. Furthermore, these pillars are divided into sub-indicators including market share, energy cost, water cost, research and development investment, gas emissions, power source proximity, reject stream characteristics, reject stream disposal, manpower, water quality, health costs and population.

The modelling framework involves expertise through surveys to evaluate the performance of the model. The specific conclusions derived from the study can be summarised as follows:

- Assessing sustainable development performance is a complex, often biased and problematic issue for desalination plant technologies. However, this can be alleviated using modern artificial intelligence methods such as fuzzy logic. The findings obtained and ranks allocated to systems based on the current research allude to the synergistic specifics of both sustainability and fuzzy logic, which when utilized in amalgamation, can be employed in any other context. This is due to the inherent flexibility of this approach.
- The arrangement of the fuzzy inference system model utilized encompasses all appreciable scenarios. Fuzzy logic presents a linguistic advantage to the ranking tool that is absent in most assessment research studies. Consequently, the linguistic adaptation enhances the attractiveness to decision-makers. It follows that the gap between model users and practitioners is becoming narrower.

- The outcomes of the ranking framework strongly support previous sustainable assessments and, moreover, highlight the need to use specific indicator sets. Concerning the UAE desalination sector, the proposed model encourages decision-makers to contemplate integrating membrane separation techniques into existing distillation plants, subsequently enhancing sustainability performance. This recommended change is critical for the UAE and other similar countries, considering the industry's predicted energy requirements and the recent deregulation of fuel resources.
- The illustrative examples used to validate the model showed that plant Y is more sustainable than plant X, which is consistent with other sustainability ranking studies.
- The proposed model has some limitations, which could be addressed in a commercial software product in the future. The flexibility and prioritization function of the indicator set could be more emphasized for the fuzzy model. The quantity and character of fuzzy inference system models utilized to structure the framework is subject to amendment and the context under which the works function. If the modelling framework would be made accessible via a user interface in a software product such as MATLAB, it would considerably boost the appeal to the desired audience, which are decision-makers.
- The fuzzy logic ranking framework provides an easy to interpret tool by which the decision-maker can rank alternative scenarios in a simple and easy-to-understand manner.
- The developed model is easy to understand and can be straightforwardly improved, adjusted or enhanced as required by adding new indicators to represent the available data for the desired desalination plant.
- It is advantageous to apply the sustainability ranking during the planning stage, as it is easier to improve sustainability during this phase.

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