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Review

Simulation and Optimization of Renewable Energy-Powered Desalination: A Bibliometric Analysis and Highlights of Recent Research

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Abstract: Seawater desalination is emerging as one of the preferred systems for dealing with the problems of freshwater scarcity, which makes it necessary to redouble efforts to obtain an optimal and competent production process. For this reason, the coupling of water desalination and renewable energy systems is not surprising. This study applied a bibliometric analysis to evaluate the research trends on desalination systems and renewable energies from an engineering approach using optimizations or simulation techniques. The Scopus database was used for this study, selecting articles published between 2009 and 2022. A general analysis was carried out regarding trends in the number of articles produced, number of citations, subject area, journals, countries, institutes, and authors. Further, a more specific analysis was then performed in terms of renewable energy technologies used and preferred optimization/simulation methods and software used. The results also revealed that the field is growing, based on the number of articles published and the increase in citations. On the other hand, it was found that the most studied renewable energies, in coupling with desalination systems and from an optimization/simulation approach, are solar and wind.

Keywords: bibliometric analysis; desalination; renewable energy; simulation; optimization

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1. Introduction

Seawater desalination is viewed as a mature technology to meet the water demands of many countries around the world. Technologies commonly used for desalination can be broadly classified as thermal or membrane-based methods. Thermal desalination technologies include multi-stage flash (MSF) desalination systems, multiple effect distillation (MED) desalination processes, and mechanical vapor compression evaporation (MVC). Membrane-based desalination includes reverse osmosis (RO), electrodialysis (ED), nano-filtration (NF), and membrane distillation (MD). Even though seawater desalination has been acclaimed as a feasible solution to the growing water demand, it remains an energy-intensive process. Reducing the high energy costs of desalination and its environmental impact requires continuous research and development. Renewable energy-powered desalination systems (RES-DSs) help produce water at costs competitive with fossil-powered desalination plants while significantly reducing greenhouse gas emissions. The interest in RES-DS appears to have increased considerably in recent years. Figure 1 illustrates different alternatives of RES-DS, which depend on the type of utility required for desalination. For instance, the steam used as a hot utility in the main brine heaters in the thermal desalination units (MSF, MED, and TCD) could be generated from solar, geothermal, and/or biomass energy, whereas the electricity required by the high-pressure pumps in membrane-based desalination processes (RO, NF, and ED) and compressor in MVC can be generated from hydro, wind, sea wave, and/or tidal energy.

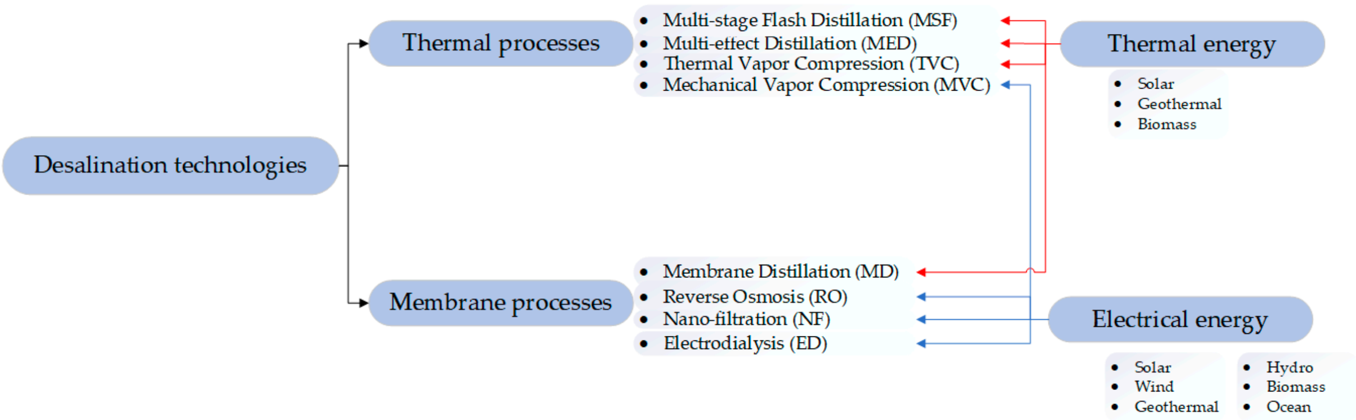

Figure 1. Main alternatives for coupling renewable energy sources (RESs) and desalination systems (DSs).

The design of an RES-DS faces several challenges. One challenge stems from the high variability and uncertainty in generating renewable energy. Renewable energy sources are weather dependent, leading to intermittency (fluctuations) in energy generation. These fluctuations will directly affect the performance of desalination units, causing unstable operation and risking insufficient energy production at the right time to meet the desired freshwater demand. Additional uncertainties stem from variability in the market price and load demand. In addition, due to climate change, population growth, seasonal migrations, etc., water demand is increasing and faces significant seasonal and annual variability. Several alternatives were proposed to address these challenges; those include storing excess energy produced at times of surplus and using it at times of an energy deficit, combining renewable and non-renewable energy sources to cover the intermittency, or combining two complementary renewable energies to guarantee the necessary energy supply. Recently, many studies have attempted to combine optimization and simulation techniques to design RES-DSs.

From the perspective of process system engineering (PSE), several researchers have proposed using simulation and optimization techniques to design effective desalination systems that rely on renewable energy. The main goal of these studies is to meet the constraints posed by relying on renewable energy and minimize the cost of production to ensure sustainable operation. Several authors employed simulation-based optimization methods by applying either specific simulation tools (mainly HOMER software) or in-house models. Usually, authors who employed HOMER [1] introduced, as input, the power consumption profile required by the DS unit, and the software matched the renewable energy generation to the required load. Simulation-based optimization methods perform many simulation runs, and then, the best solution is obtained by comparing the values of the desired metric(s). Thus, the best solution is obtained from simulation runs without any degrees of freedom. Alternatively, researchers have explicitly stated the RES-DS design to be a simultaneous optimization problem by proposing an objective function to be maximized (or minimized), subject to several constraints, such as mass, energy, momentum balances, and cost equations. Compared to simulation-based optimization approaches, in the simultaneous optimization approach, the trade-offs between the system variables are optimized simultaneously, reducing the possibility of excluding interesting solutions from the search space.

There are several important considerations to successfully apply optimization and simulation techniques in designing RES-DSs. Essential information requires the stochastic forecasting of the electrical power available from the RES and seasonal water demands.

Thus, system data collection and processing strongly influence the validity of the simulated/optimized solution. Furthermore, the selection of time and spatial scales to consider the relevant climatic changes, investment periods, and standard periods plays an important role in the validity of the solution. For example, the choice of the temporal scale (seasonal, daily, and/or hourly) depends on variations in the demands and factors influencing energy generation during the period. Thus, spatial and temporal variations are often the main challenge associated with the mathematical modeling of an RES-DS [2]. In addition, there is an important trade-off between including high-resolution data (spatially and temporally) and the computational tractability of the mathematical model. Some authors have taken data from NASA's POWER (Prediction of Worldwide Energy Resource) database as representative data for the climatological conditions and considered the hourly weather variation by linking the database with the RES-DS models [3]. Other authors simplified the information by considering daily or monthly variations [4].

In the open literature, recent review articles [5,6] have looked at the different aspects of RES-DS design. Some authors paid attention to given pieces of equipment, such as solar chimneys for desalination [7]. In addition, other authors focused on fixed renewable energy combined desalination techniques, including different combinations of renewable energy sources and types of desalination plants [8], for instance, typical PV-RO and PV-ED systems [9], stand-alone desalination processes (MED, multi-stage flash (MSF)), and thermal vapor compression (TVC) [10]. A review of the application of artificial intelligence in decision-making, optimization, prediction, and control of four desalination processes can be found in He et al. (2022) [11].

However, despite such review articles, no detailed study has employed a computer-assisted bibliometric analysis to quantitatively assess current research trends on simulation and/or optimization for renewable energy-powered desalination systems. Bibliometric analysis is the statistical evaluation of published scientific literature to measure the influence of publications in the scientific community [12]. Bibliometrics can be used to identify research strengths and inform decisions about future research interests. Two articles addressing bibliometric analysis can be found in the seawater desalination area. Naseer et al. [13] presented a recent bibliometric analysis of stand-alone desalination technologies considering the last two decades. The analysis was performed without considering renewable energy. Sonawane et al. [14] presented a bibliometric analysis of the application of computational fluid dynamics (CFD) for the simulation of solar desalination systems. No in-depth study quantitatively assessing current research trends in simulation and/or optimization for renewable energy-powered desalination systems was found. Therefore, this paper intends to fill this research gap by proposing a bibliometric analysis of literature published on that topic for 2009–2022, where a significant increase in the number of publications and citations was observed. In addition, keyword analysis will be used to identify thematic clusters in which different modeling approaches can be grouped. More importantly, articles employing the simulation approach will be distinguished from those using the simultaneous optimization approach, indicating the computational tool (software tool) used in each case. In addition, when optimization is addressed, the analysis will distinguish between single-optimization and multi-objective optimization, indicating the objective functions considered in each case.

In summary, the main interest of this paper is to conduct a bibliometric analysis to answer the following research questions:

RQ1: What trends can be detected when analyzing studies on simulating/optimizing seawater desalination processes using renewable energy?

RQ2: Who are the major contributors to research in the simulation/optimization area of such processes?

RQ3: What are the recent advancements and research gaps/future directions?

The structure of this paper involves several sections. Section 2 provides a brief background on mathematical modeling, simulation, and the optimization of renewable energy-based desalination, including challenges in optimizing renewable energy-based desalination. Section 3 discusses the methodology implemented in this research, including details on the data extraction, trend analysis, co-citation analysis, and content analysis. Section 4 presents and discusses the results of the bibliometric analysis. Finally, Section 5 provides highlights of recent developments and research opportunities in the field of simulation and optimization of seawater desalination using renewable energy.

2. Background

2.1. Simulation and Optimization

Optimization can be defined as ensuring that one or more objectives are achieved by using the available resources in the system in the most efficient way. Two significant aspects of optimization are mathematical modeling and analysis. Mathematical modeling translates a problem faced in real life into a set of equations to describe the problem correctly, and analysis includes achieving the best solution for the model [6]. Today, most studies on optimization are carried out using different analysis methods and algorithms.

Optimizing any process or system can be carried out considering a single objective function or multi-objective functions. In any case, the system is expected to yield better performance within its physical and technical constraints. In the RES-DS, the performance indicators mostly used as single objective functions are as follows: (i) energy requirement and consumption by the desalination process; (ii) cost of production of freshwater using different cost matrices; (iii) permeate flux rate; (iv) volume of freshwater production; (v) brine handling and treatment; (vi) environmental impacts of both the energy sources and desalination process. However, the performance indicators commonly used as multi-objective functions result from combining more than one of the performance indicators mentioned above.

Optimization problems can be classified according to several aspects: (i) a static or dynamic (parameter or trajectory) problem depending on the nature of design variables; (ii) constrained or unconstrained according to the existence of constraints; (iii) optimal control or non-optimal control depending on the physical structure of the problem; (iv) linear programming, nonlinear programming, quadratic programming, or geometric programming depending on the type of equation formulated; (v) integer programming or non-integer programming depending on the type of variables involved; (vi) separability of functions, separable or non-separable programming; (vii) the deterministic nature of the variables, stochastic (with uncertain variables) or deterministic (with known parameters or variables); and (viii) single or multi-objective problems depending on the number of objective functions considered. Usually, RES-powered desalination systems involve mostly a combination of different optimization problems: constrained, deterministic, nonlinear, and optimal control.

One important aspect is the selection of the appropriate optimization algorithms that suit the nature of the problem to be solved. A classification of the optimization algorithms applied for RES-DS is summarized in Figure 2.

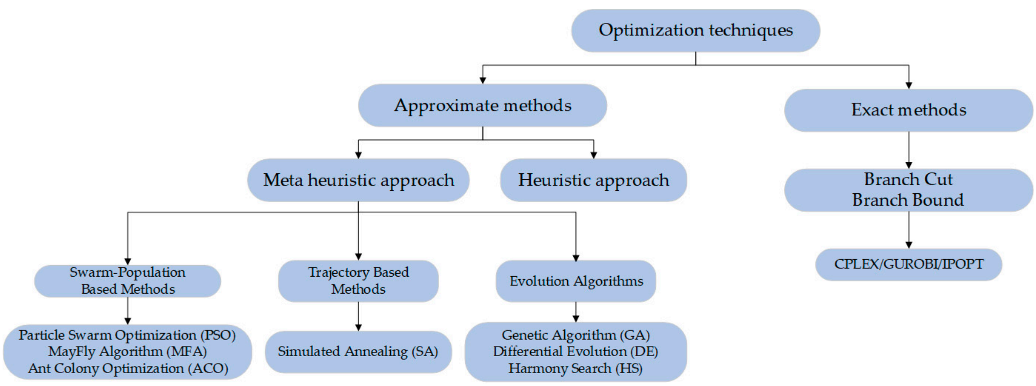

Figure 2. Major optimization algorithms applied for RES-DS.

As observed in Figure 2, heuristic and metaheuristic algorithms are approximate methods and have been proposed as alternatives to overcome the computational drawbacks of the existing exact methods. The approximated methods use probabilistic transition rules instead of deterministic rules and are developed by mimicking several scenarios.

PSO was derived by studying the predation behavior of bird or fish swarms and applications for RES-DSs [15]. Malisovas and Koutroulis [16] used the PSO algorithm to minimize the total lifetime cost of the grid-connected RES-DS powered by a grid-connected hybrid PV/Wind renewable energy system. Compared with other evolutionary optimization techniques (e.g., genetic algorithms, firefly algorithm, etc.), the authors concluded that the PSO algorithm exhibits relative implementation simplicity and effectively solves complex nonlinear optimization problems.

Applications of MFA can be found in [17] who compared the performance of MFA to eight other proven algorithms [Particle Swarm Optimization (PSO), Genetic Algorithm (GA), Differential Evolutionary Algorithm (DE), Ant Lion Optimization (ALO), Grey Wolf Optimization (GWO), Dragonfly Algorithm (DA), Grasshopper Optimization Algorithm (GOA), Moth Flame Optimization (MFO)]. The authors solved a single-objective mathematical model that minimizes the annual leveled cost to find the optimum configuration and size of the PV-BES among six configurations. Comparison results show that MFA provided the global best optimal values in all six configurations and demonstrated better robustness and fast convergence efficiency in finding the global optimal solution.

Regarding GA, Barek et al. [18] addressed the minimization of the lifetime round total system cost of an RO desalination unit driven by hybrid PV/Wind systems to cover a fixed desalinated-water demand. The authors successfully showed the capacity of the GA to obtain the solution corresponding to the global optimum with a relatively simple calculation. Among a list of commercially available system devices, the proposed model and GA implementation allow the optimal number and type of PV modules, wind turbines, and batteries to be obtained.

Regarding HS and SA, Zhang and Maleki [19] combined both algorithms to investigate the optimal design of the stand-alone hybrid energy scheme based on a small-scale ROD unit to minimize the total net annual cost, environmental damage, and the probability of loss of load supply. Moreover, Zhang et al. [20] successfully combined SA with Chaotic Search Algorithms (CSAs) to address the minimization of the life cycle cost of small reverse osmosis (RO)-based desalination plants driven by wind and solar energies. The authors concluded that hybrid algorithms yield more beneficial results than the CSA and original SA algorithms.

2.2. Challenges in Renewable Energy-Based Desalination

As was briefly mentioned in the introduction section, one of the constant and greatest challenges in renewable energy-based desalination is the fluctuating existence, which is entirely dependent on climate fluctuation and may result in load refusal in some places [21].

The operation mode of any desalination system at variable energy loads leads to low efficiencies and plant operating life. The energy requirement of any desalination system must be constant and continuous. Therefore, the intermittency associated with power output from any renewable energy systems is the main limitation of the low adoption of renewable energy for desalination [22]. Then, an energy storage system or an additional backup source of energy is required to operate the desalination units continuously at a constant load. Energy storage systems help to store surplus energy during on-peak power output time and release it during off-peak times.

The use of solar energy for seawater desalination depends strongly on the capacity scale. Currently, for very large-scale applications, desalination using solar energy only is not a viable solution, either technically and/or economically [23]. It can be suitable in remote locations without an electric grid connection for small- and medium-scale applications. However, the operation and maintenance of these technologies require skilled operators. In small-scale systems, PV panels and wind turbines may be combined to exploit each sub-system's advantages towards reducing the overall cost. For large-scale systems, concentrating solar thermal power (CSP) plants with thermal energy storage and fuel co-firing can provide stable operation of the desalination units.

2.3. Challenges in Optimizing Renewable Energy-Based Desalination

Significant research efforts are being directed towards the challenging tasks for exploring and proposing strategies and models to maximize advantages while minimizing drawbacks in optimizing renewable energy-based desalination systems. The emergence of RESs poses uncertainties, leading to stringent requirements for system modeling and operation practices. High variability and uncertainties in renewable power generation, which mainly depend on the variable properties of wind and solar, market price, and load demand, are inevitable and significant issues representing the major challenges to developing optimization models. The model needs to be sufficiently detailed to account for hourly variations, differences between days of the week, seasonality, and long-term planning and investment. To ensure that RES-powered desalination systems work continuously, their various specifications must be fully considered in the design process. Over the life of an energy system, market prices, such as electricity, natural gas, and oil, are unlikely to remain stable and will vary with changes in the energy, climate, economy, and global and local mark. Load power is highly time-dependent, including deterministic components that are reproducible and influenced by factors, such as time and weather and random components derived from prediction and measurement errors.

Finally, it is important to highlight from the model implementation and solution strategy point of view that the selection of the time scale to consider the climatic changes plays an important role in the efficacy of successfully solving optimization problems of renewable energy-powered desalination processes. In this sense, another relevant challenge in optimizing renewable energy-powered desalination is the development of a mathematical model that is as detailed as possible, but at the same time, it can be tractable and solved easily using the optimization algorithm. It is well-known from the mathematical modeling point of view that the computational cost (i.e., the number of constraints and variables, CPU time, model convergence) increases significantly with the increase in the level of details involved in the description of the behavior of a sub-system. In addition, it is desired that all the trade-offs involved in optimizing RES-powered desalination can be optimized simultaneously using exact methods.

3. Methodology

The research conducted in this paper is based on a bibliometric analysis of the relationship between renewable energy desalination and optimization and/or simulation methods.

3.1. Data Collection

Database selection is a fundamental part of a reliable and quality bibliometric analysis. All data presented in this paper were extracted from Scopus [24]. This is an abstracting and indexing database with full-text links produced with more than 27,100 active serial titles, including articles, books, and conference papers. Scopus was chosen primarily because it is considered an extensive, high-quality, and reliable database with broad coverage in the areas of interest of this study, such as science and engineering [25]. In addition, it has the advantage of a user-friendly interface for entering search filters and easy data extraction, and it provides a data analysis tool. The resulting data presented in this paper are based on the following search: TITLE (desalination OR desalting OR desalinization) AND KEY ((optimization OR simulation)) AND TITLE-ABS-KEY ((renewable) AND (energy OR energies OR resource))). This search focused on research on desalination, renewable energies, and specific works with an engineering approach, applying optimization and/or simulation methods, obtaining a total of 214 articles. The literature corresponding to this group consisted of 160 articles, 37 conference papers, 11 reviews, 4 book chapters, 1 book and 1 review. English is the most used language, with 98.59% of the published research papers. Therefore, the field of study was limited to articles and writings in English. Analyzing the trend, between 1995 and 2008, the number of publications had no marked trend, with years in which the production of articles in the field of study was nil (1996, 1997, 1998, 2000, 2002, and 2008). Then, from 2009 to 2022, productivity increased, in all years, by almost ten-fold. For these reasons, this research will analyze all articles between 2009 and 2022. As a result, 139 articles were identified in this field of study that were written in English.

3.2. Data Analysis

Bibliometric analysis consists of two parts: performance analysis and scientific mapping. The performance analysis reports the contributions of the different research components, while the scientific mapping shows a graphical representation of the relationship between these components [26].

3.2.1. Performa Analysis

For the analysis of the extracted information, different tools were used. For performance analysis, the Scopus results analysis system was used, which provides information, such as the number of documents per year, number of citations per year, documents per year per source, documents per author, and documents per affiliation, per country, and subject area. In addition, Scopus contains different metrics [27] that help to better understand the impact of research. The metrics used in this study are presented below.

- CiteScore: measures the impact of a citation of a title (journal, book, conference proceedings, etc.). Using this indicator for 2018–2021 since, at the time of this research, it was not updated to 2022.

$$CiteScore\ 2021 = \frac{Citations\ 2018 - 2021}{Documents\ 2018 - 2021} \tag{1}$$

- CiteScore Percentile: Indicates the relative standing of a title in its subject field and corrects for the different sizes of subject fields.
- CiteScore rank: Indicates the absolute standing of a title in its field.
- H-index: Evaluates the performance of a scientist. It considers the number of articles published and the quality represented by the total number of times their articles were cited.

Data processing was also carried out using Microsoft® Excel® (Version 2302), exporting the database from Scopus as a CSV file.

3.2.2. Scientific Mapping

For a better understanding of the extracted data, scientific mapping was performed. Scientific mapping or bibliometric networks is a spatial presentation that permits us to appreciate how disciplines, fields, specialties, and individual articles or authors are related by their physical proximity and relative location [28]. The VOSviewer software (version 1.6.18) was used to analyze collaborations between countries and collaborations between authors. In addition, the data mining functionality of this tool can be used to construct and visualize the co-occurrence of terms extracted from the literature. The steps followed for this bibliometric analysis are condensed in Figure 3, and the following section details the search strings used.

3.3. Analysis

The results obtained by applying performance analysis and scientific mapping techniques were used to determine the research trend and the more influential components (authors, countries, institutes, journals, documents etc.); with this information, the research gaps were identified, and future directions were established. Figure 3 condenses the main steps described in Section 3.

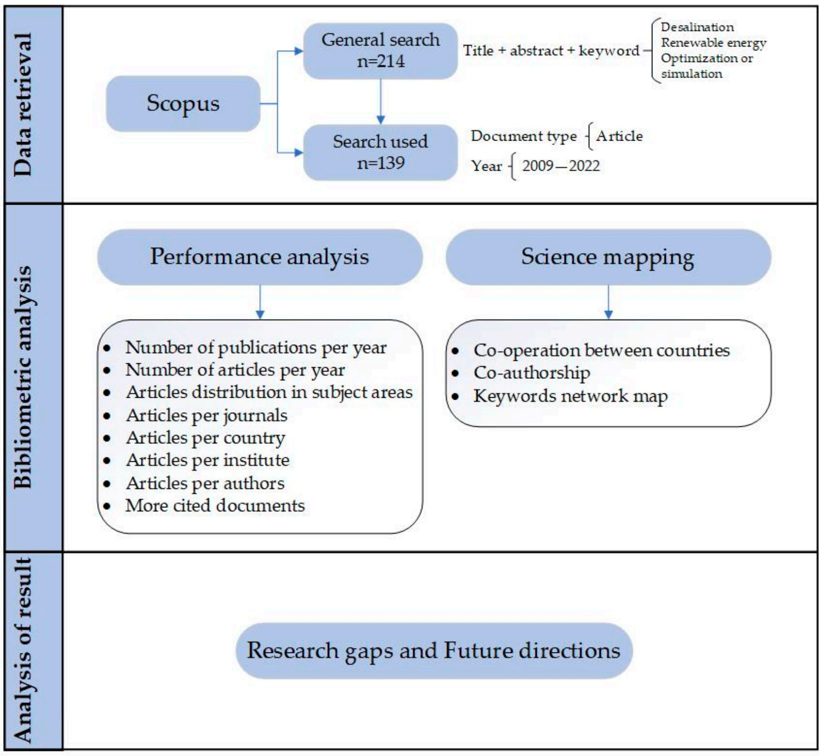

Figure 3. Study flowchart.

4. Results and Discussion

4.1. Publication Trend

The total production and total citations per year were analyzed to evaluate the evolution and trend in this field of study from 2009 to 2022. Figure 4 shows the annual distribution of these metrics for 139 articles [3,15–20,29–160]. The year 2021 presents the highest number of published articles (34 articles), 24.88% of the total number of articles produced in the specified period. Regarding the total citations, 3415 citations were registered, excluding self-referenced citations, with 2022 being the year with the highest number of citations (822 citations).

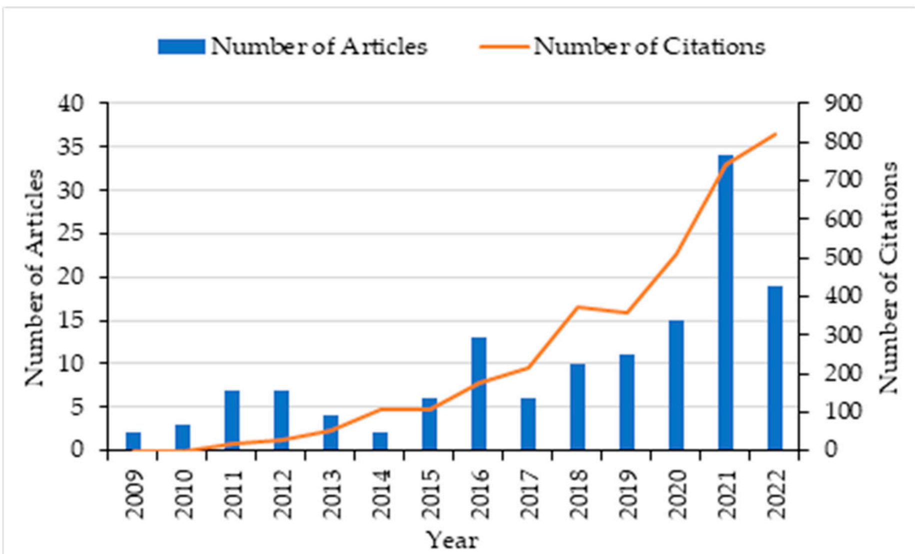

Figure 4. Total number of articles published under desalination and renewable energies applying optimization or simulation as a resolution method. Data extracted from Scopus for the period 2009–2022.

In 2022, there was a decrease of 44% in the total article production compared to that in the previous year. An analysis was carried out to identify the reason for this phenomenon by conducting a more general search in Scopus (TITLE (desalination OR desalting OR desalinization) AND KEY (optimization OR simulation)). Considering the years 2021 and 2022, with an emphasis on the detection of other focal fields, a graphical study was carried out using the Vosviwer software (Figure 5). In the year 2021, the existence of three clusters, the main one dedicated to desalination (red) and two secondary clusters dedicated to renewable energies (blue) and specific studies on desalination membranes (green), can be noted, competing for these areas directly; however, in the year 2022, the topics related to renewable energies show lower importance being absorbed by the main cluster and taking the relevance of the cluster focused on the study of membranes. Therefore, it could be inferred that the field of desalination-optimization/simulation in the year 2021 presented an upward trend in works focused on desalination systems with a special focus on energy problems and renewables, while in 2022, there was a more marked trend in the studies applied to desalination membrane technologies.

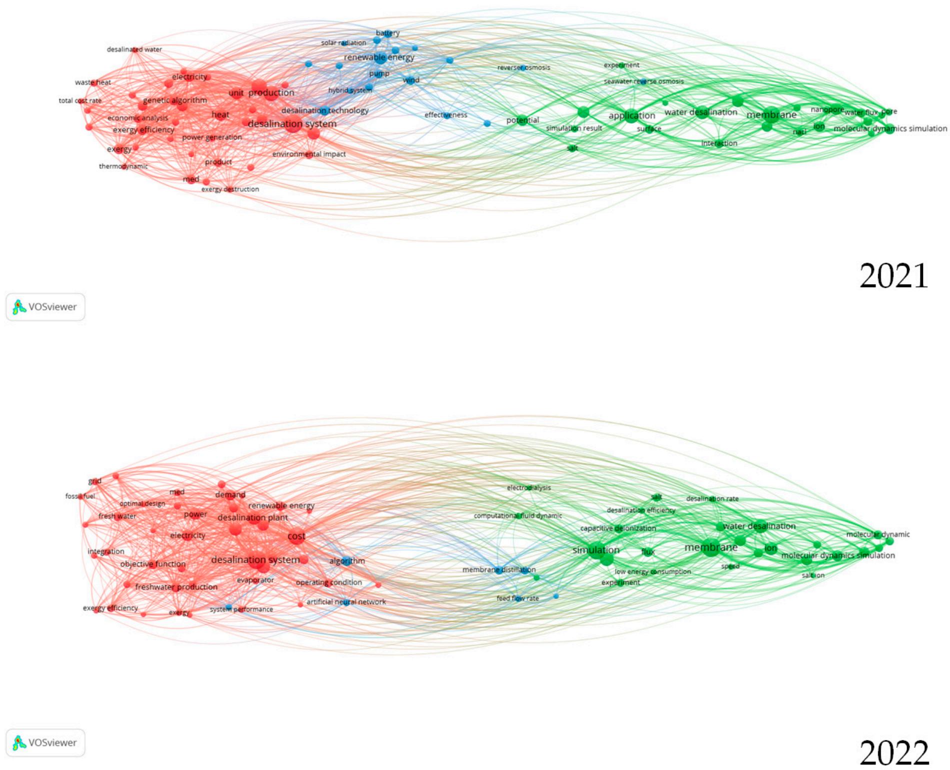

Figure 5. Network map based on keywords based in the search: TITLE (desalination OR desalting OR desalinization) AND KEY (optimization OR simulation). Data were extracted from Scopus for 2021 and 2022, and the graph was developed with VOSviewer.

The current body of literature on renewable energy-based desalination is relatively limited compared to that of conventional seawater desalination. However, with technological advancements and heightened research activities, it is anticipated that the number of publications in this domain will steadily rise. Consequently, comparing the number of articles between renewable energy-based and conventional energy-based desalination technologies may not serve as a fair indicator and can potentially result in inaccurate assumptions or conclusions.

4.1.1. Article Distribution in Subject Areas and Journals

The subject area is directly related to the categories in which the journals are indexed, which is an excellent indicator of the point of view from which the articles are approached.

The articles are classified into 17 areas, which are shown in Figure 6. The more influential fields are Engineering (76 articles), Energy (72 articles), Environmental Science (70 articles), Chemical Engineering (31 articles), and Materials Science (30 articles). Table 1 lists the journals with the highest number of articles. Other indicators provided by Scopus related to Source details are also reported: CiteScore, Number of documents in all categories in the period 2018–2021, Scopus source categories, and CiteScore rank per source categories.

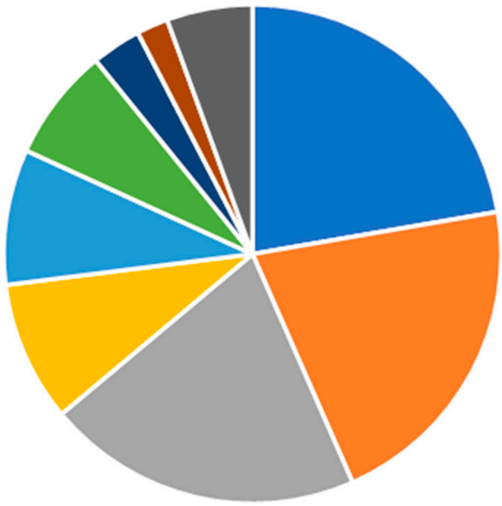

Figure 6. Distribution of articles by subject area. Data were extracted from Scopus for the period 2009–2022.

Table 1. The six most productive journals ordered by the number of articles. Data were extracted from Scopus for the period 2009–2022.

Rank	Journal	Number of Articles	CiteScore 2021	Scopus Source Categories	CiteScore Rank
1	Desalination	20	16.3	Water Science and Technology	4/237
				Mechanical Engineering	11/601
				General Chemical Engineering	9/208
				General Chemistry	25/409
				General Materials Science	29/455
2	Energy	14	13.4	Modeling and Simulation	5/303
				Civil and Structural Engineering	7/326
				Management, Monitoring, Policy and Law	8/376
				Mechanical Engineering	18/601
				Building and Construction	7/211
				Industrial and Manufacturing Engineering	13/338
				Fuel Technology	6/109
				Energy Engineering and Power Technology	14/235
				Pollution	10/144
				General Energy	5/68
				Electrical and Electronic Engineering	36/708
3	Renewable Energy	12	13.6	Renewable Energy, Sustainability, and the Environment	21/215
4	Desalination and Water Treatment	11	1.7	Ocean Engineering	55/98
				Water Science and Technology	147/237
				Pollution	99/144
5	Energy Conversion and Management	10	18.0	Nuclear Energy and Engineering	2//64
				Energy Engineering and Power Technology	7/235
				Fuel Technology	4/109
				Renewable Energy, Sustainability, and the Environment	11/215
6	Applied Energy	7	20.4	Building and Construction	1/211
				Management, Monitoring, Policy, and Law	2/376
				Mechanical Engineering	7/601
				General Energy	3/68

As can be observed in Table 1, Desalination is the most influential journal in terms of the number of articles, with 20 articles, followed by Energy, with 14 articles. From the list of the six journals presented, Energy is the most productive journal, with 9305 articles in 2018–2021 and a CiteScore percentile between 90 and 98 in its subject areas. On the other hand, Applied Energy is the most influential journal, with a CiteScore index of 20.4 and with CiteScore percentile between 96 and 99 in its subject areas.

4.1.2. Countries, Institutions, and Authors

The geographical distribution of publications is an important metric to know how research efforts are distributed worldwide. It can be observed in Figure 7 that only a few countries participate in this research topic (48 countries), where 35.4% have more than five publications and only 18.8% have more than ten publications.

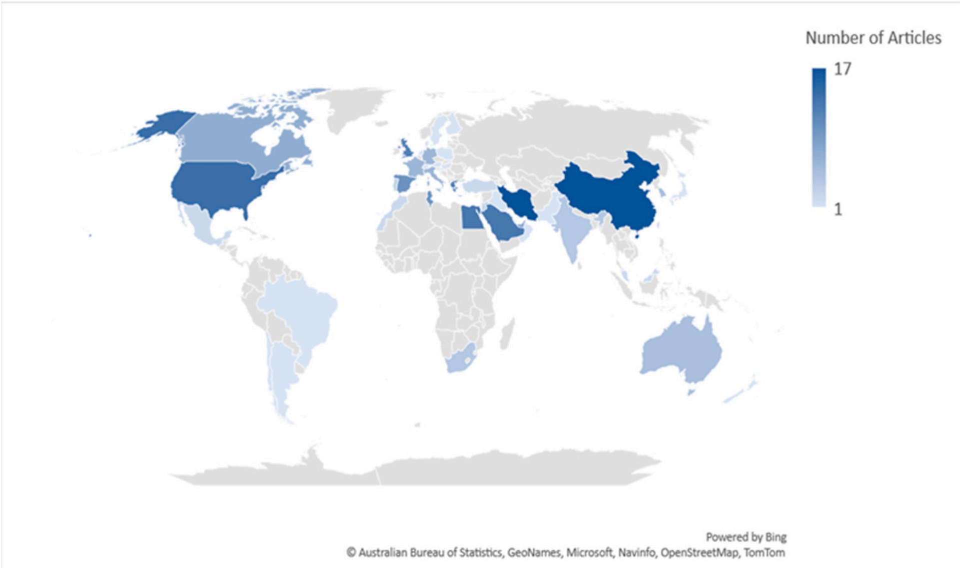

Figure 7. Distribution of articles by country. Data were extracted from Scopus for the period 2009–2022.

Table 2 shows the 16 countries with more articles and citations. Iran and China head the list with 17 articles each, followed by Egypt, the United States, and Saudi Arabia. In the case of China, the year 2021 was the most productive year, with five articles; in the case of Iran, 2021 and 2022 were the most productive, with five articles each year. In addition, Iran is the country with the highest number of citations (589), followed by Egypt (476) and the United States (372).

Table 2. The most productive countries by number of articles and number of citations. Data were extracted from Scopus for the period 2009–2022.

Rank	Country	Number of Articles	Rank	Country	Number of Citations
1	China	17	1	Iran	589
1	Iran	17	2	Egypt	476
2	Egypt	14	3	United States	372
2	United States	14	4	Saudi Arabia	354
2	Saudi Arabia	14	5	Greece	353
3	Greece	12	6	China	312
3	United Kingdom	12	7	Italy	287
4	Spain	10	8	Canada	259
4	Tunisia	10	9	France	251
5	United Arab Emirates	8	10	Spain	241

Table 2. *Cont.*

Rank	Country	Number of Articles	Rank	Country	Number of Citations
6	Canada	7	11	Tunisia	235
6	Germany	7	12	United Kingdom	234
7	Italy	6	13	United Arab Emirates	188
7	France	6	14	Australia	147
8	Australia	5	15	South Korea	123
8	South Korea	5	16	Germany	24

A total of 48 countries produced the 139 articles studied. Sixteen countries have at least five publications, from which a bibliometric network was constructed using VOSviewer to analyze co-authorship and countries (Figure 8). The size of the circles represents the number of articles produced by that country, the lines connect the countries that have co-produced articles, and the distance between nodes reflects the strength of co-authorship, with nodes being closer together with a greater number of co-authored articles and colors indicating clusters of closely associated countries [161,162]. According to the above, the bibliometric mapping shows that China and Iran are the most productive countries. Regarding country–coauthor cooperation, the UK is the most cooperative country, with 15 collaborations with Spain, Australia, Germany, Egypt, United Arab Emirates, Saudi Arabia, Iran, Canada, Italy, and Tunisia. It is followed by China and Egypt, both with 11 collaborations, Saudi Arabia (9), Iran (9), and the United Arab Emirates (8).

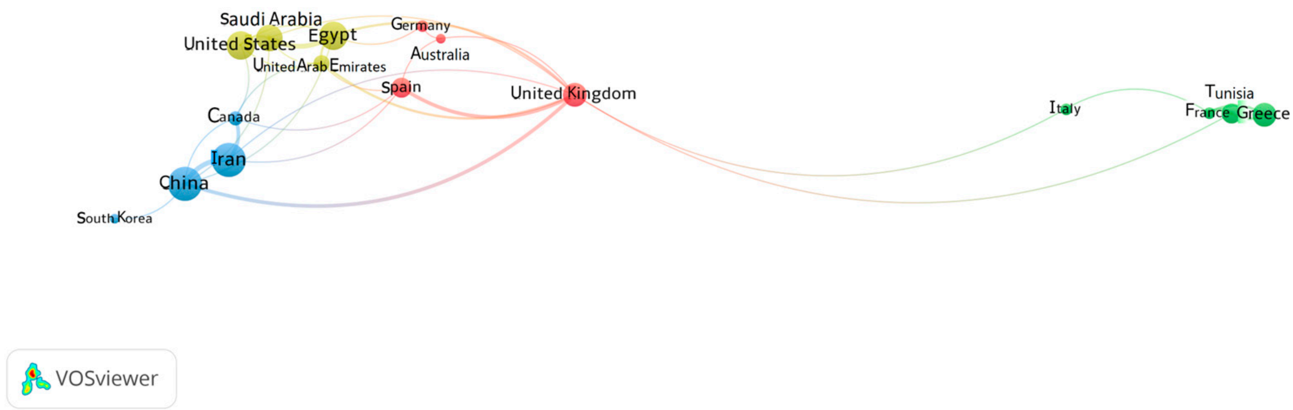

Figure 8. Network map for co-authorship and countries. Data were extracted from Scopus for 2009–2022, and graphs were developed with VOSviewer.

Table 3 shows the ranking of institutes with more than four papers in this field. The University of Tehran (Iran) has the most publications, with nine papers. The University of Tunis El Manar from Tunisia (6) and King Fahd University of Petroleum and Minerals from Saudi Arabia (5) follow it.

Out of a total of 435 authors, it is observed that only 14 (3.2%) have more than 3 articles in the field of study. The authors who contributed the most are listed in Table 4, headed by Prof. Maleki A. with 7 papers, who also is the author with the highest number of citations, with 590 citations, followed by Prof. Koutroulis E. with 5 papers and 114 citations.

Table 3. The 13 most productive institutions ranked by number of articles using a cut-off of more than 4. Data were extracted from Scopus for the period 2009–2022.

Institutes	Country	Number of Articles
University of Tehran	Iran	9
The University of Tunis El Manar	Tunisia	6
King Fahd University of Petroleum and Minerals	Saudi Arabia	5
Massachusetts Institute of Technology	United States	5
Technical University of Crete	Greece	5
The National Engineering School of Tunis	Tunisia	5
National Technical University of Athens	Greece	4
The University of Las Palmas de Gran Canaria	Spain	4
Technical University of Berlin	Germany	4
Queen's University Belfast	United Kingdom	4
The Higher National Engineering School of Tunis	Tunisia	4
Tunis University	Tunisia	4
University of Sharjah	United Arab Emirates	4

Table 4. The most contributing authors, ordered by the number of articles, using a cut-off of three contributions. Data were extracted from Scopus for the period 2009–2022.

Rank	Author Name	Number of Articles	Citation	Present Affiliation	H-Index
1	Maleki, A.	7	590	Shahrood University of Technology, Semnan, Iran	40
2	Koutroulis, E.	5	114	The Technical University of Crete, Chania, Greece	27
3	Belhadj, J.	4	45	The University of Tunis El Manar Tunis, Tunisia	16
4	Cao, J.	3	31	Luxembourg Institute of Science and Technology, Esch-sur-Alzette, Luxembourg	18
5	Cherif, H.	3	8	The National Engineering School of Tunis, Tunis, Tunisia	5
6	Littler, T.	3	31	Queen's University Belfast, Belfast, United Kingdom	24
7	Malisovas, A.	3	10	Technical University of Crete, Chania, Greece	2
8	Okampo, E.J.	3	18	University of Johannesburg, Johannesburg, South Africa	5
9	Papadakis, G.	3	102	The Agricultural University of Athens, Athens, Greece	44
10	Rosen, M.A.	3	187	Ontario Tech University, Oshawa, Canada	92
11	Yang, D.	3	31	College of Information Science and Engineering, Northeastern University, Shenyang, China	20
12	Zhou, B.	3	31	Northeastern University, Shenyang, China	14

In addition, by analyzing the h-index (the h-index is a metric that measures the productivity and citation impact of publications by author), Rosen, M.A. is the most influential author in this group, following Papadakis, G. and Maleki, A. Similarly, to the network generated to analyze the relationship between countries, a network is constructed to explore the relationship between authors. Analyzing the 435 authors using VOSviewer, 97 clusters are identified, with no interaction between them (Figure 9). It can be noted that the interrelationship between different research groups is poor to null.

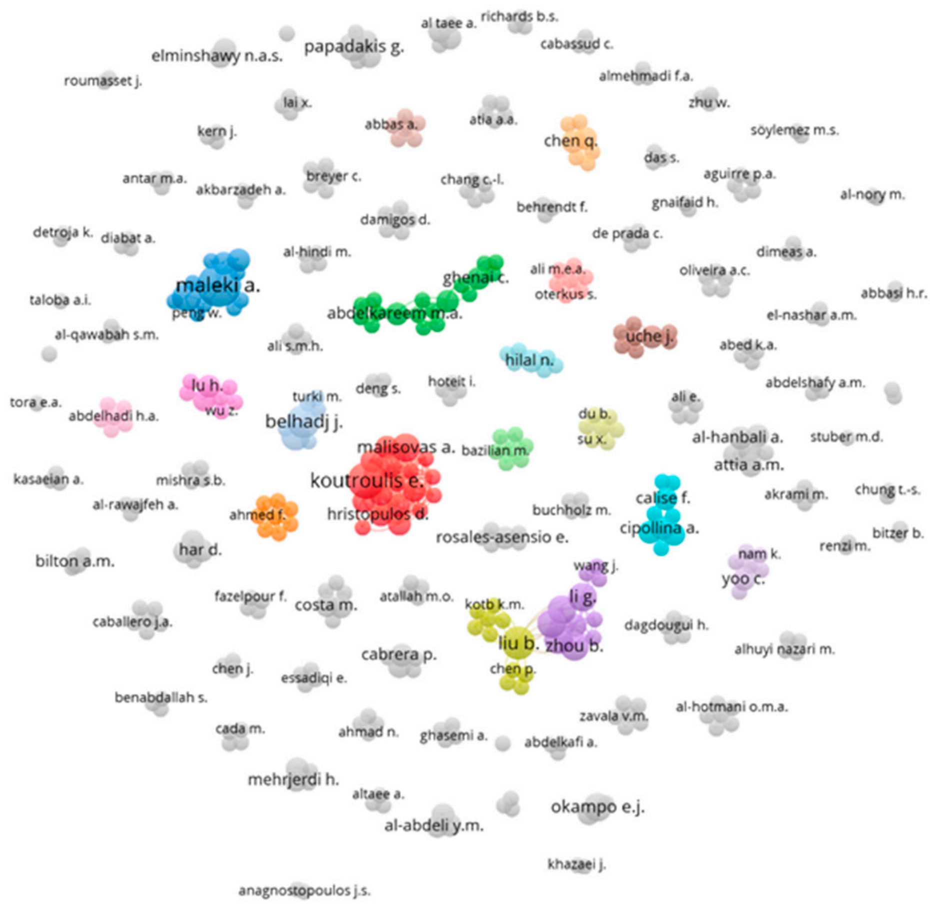

Figure 9. Network analysis diagram of co-authors. Data were extracted from Scopus for 2009–2022, and the graph was developed with VOSviewer.

4.1.3. Analysis of Recent Articles with Most Citations

To comprehensively explore the latest developments in the field of study, a detailed analysis of the most recent papers published between 2018 and 2022, along with their corresponding citation counts during the same period, is proposed. Table 5 provides a concise summary of the key information pertaining to the most influential works. The paper garnering the highest number of citations is "Design and optimization of autonomous solar-wind-reverse osmosis desalination systems coupling battery and hydrogen energy storage by an improved bee algorithm" [96] with 186 citations. Overall, the predominant topic in the five articles revolves around the hybridization of renewable energies as a primary energy source for desalination plants, in particular solar and wind energy, together with the integration of energy storage technologies. Since these are renewable energy systems, the integration of energy storage technologies, such as batteries [3,20,62,78,96], is proposed. Furthermore, Maleki and Abdelshafy [78,96] explored the use of surplus energy for hydrogen generation, which can be used as an alternative energy source when needed. In addition, integration with non-renewable energy-generating systems, such as diesel generators [62,78] is considered to enhance system reliability. On the other hand, the five works propose the possibility of adding water-storage tanks to the configuration, with the aim of using the surplus energy to produce extra water, increasing the reliability of supply to the consumer.

Table 5. The most cited articles in the years 2018–2022, ordered by number of citations. Data were extracted from Scopus for the period 2018–2022.

Rank	Article Title	Number of Citations
1	Design and optimization of autonomous solar-wind-reverse osmosis desalination systems coupling battery and hydrogen energy storage by an improved bee algorithm [96]	186
2	Optimal design of a grid-connected desalination plant powered by renewable energy resources using a hybrid PSO–GWO approach [78].	142
3	Optimization of a hybrid system for solar-wind-based water desalination by reverse osmosis: Comparison of approaches [3].	116
4	Simulated annealing-chaotic search algorithm based optimization of reverse osmosis hybrid desalination system driven by wind and solar energies [20].	96
5	Optimal sizing and techno-enviro-economic feasibility assessment of large-scale reverse osmosis desalination powered with hybrid renewable energy sources [62].	91

With respect to resolution methods, researchers are inclined towards optimization over simulation, with the use of approximation algorithms (Bee Algorithm [3,96], Particle Swarm Optimization [3,78], Grey Wolf Optimizer [78], Simulated Annealing [3,20], Chaotic Search [3,20], Tabu Search Algorithm [3]). Giving added value by comparing the performance of different optimization algorithms [3,20,78], the articles applied these techniques to find optimal solutions in terms of system sizing, operation, and efficiency.

The evaluation of the technical, economic, and environmental feasibility of desalination systems powered by renewable energy sources is a crucial aspect highlighted in these articles. The objective function in the five works is to reduce total costs, taking into consideration investment, operation, maintenance, and replacement costs. Regarding environmental impact, only Abdelshafy and Elmaadawy [62,78] incorporate environmental constraints concerning the utilization of non-renewable energy-generating systems, in both cases the addition of diesel generation. Given that the systems in question generate both water and energy, two distinct approaches can be considered. The first approach focuses on exclusive electricity generation to meet the demands of the desalination plant, which is considered by Peng and Elmaadawy [3,62]. On the other hand, Maleki, Abdelshafy, and Zhang [20,78,96] explore the water–energy nexus by addressing the design of a multipurpose plant capable of producing two end products: water and energy.

4.1.4. Keywords Analysis

The keywords of the 139 articles were extracted from Scopus, and a network graph was created with the VOSviewer program. Out of 1560 words, 52 meet the criterion of having more than 10 co-occurrences. The generation of the keyword map using VOSviewer is based on the use of probabilistic latent semantic analysis [163], which shows which are the most frequent words (represented by the size of the node), the most frequently associated words forming the cloisters (identified by colors), and the interconnection that exists between the keywords (lines) within the same cluster or with neighboring cloisters.

By analyzing the generated conceptual word map (Figure 10), the words with the highest frequency of occurrence are desalination, renewable energy, optimizations, reverse osmosis, solar energy, water filtration, alternative energy, photovoltaic system, renewable resource, and seawater. Four clusters can be seen; the green cluster represents research focusing on desalination followed by renewable energy and optimization. The main nodes in the red cluster are reverse osmosis, water filtration, photovoltaic system, and cost, with peripheral nodes, such as life cycle, cost analysis, economic analysis, etc. The red cluster is mainly associated with studies that relate reverse osmosis systems with solar energy from an economic point of view. Renewable resources, distillation, energy resource, design, and simulation are the most frequently occurring words in the blue cluster, which consists of smaller nodes, such as experimental studies, design, and numerical modeling. The blue cluster groups represent the main theme area related to design and experimental study around renewable energies. The yellow cluster is the smallest and consists of five elements: solar energy, wind energy, water, wind turbine, water treatment, and algorithm. The yellow group shows that the most used renewable energy is solar energy, followed by wind energy.

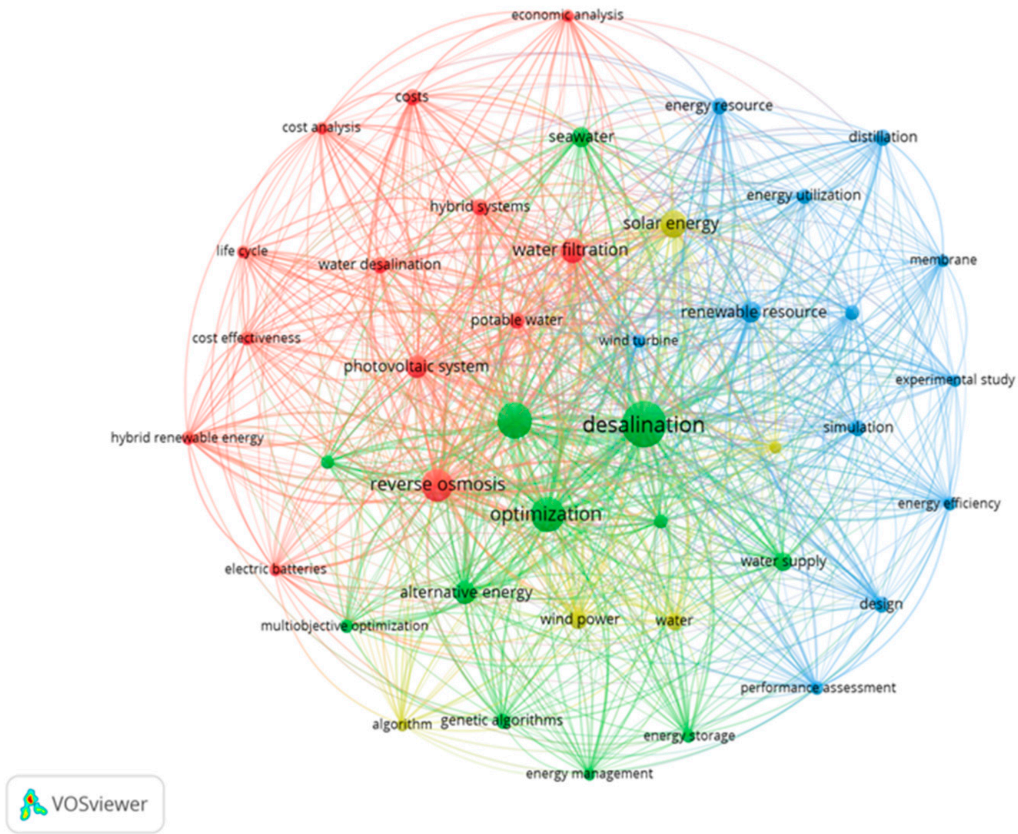

Figure 10. Network map based on keywords. Data were extracted from Scopus for 2009–2022, and the graph was developed with VOSviewer.

4.2. Trends in Renewable Energy

In this section, the aim is to identify which renewable energy technologies are the most widely used. For this purpose, an internal search by title or keyword is carried out to determine the technologies used. For each technology, different representative keywords were selected: solar energy ("solar" or "photovoltaic"), wind energy ("wind"), geothermal energy ("geothermal"), ocean energy ("wave energy" or "ocean thermal energy" or "ocean thermocline" or "tidal"), biomass energy ("biomass" or "biodiesel" or "bioenergy" or "biofuel"), hydro energy ("hydro"). Considering the possibility that some articles work with hybrid renewable energy systems (HRESs), combinatorial searches were carried out among the five types of energy under study. Considering separately the studies using only one type of energy and combining two types of energy, it is observed in Figure 11 that the most studied technology in this field of study is the combination of solar and wind energy, with 41% of the total number of studies, followed by the exclusive use of solar energy, with 33.6% of the total number of studies, followed by a low percentage of studies that focus on wind energy as the only renewable energy to be used.

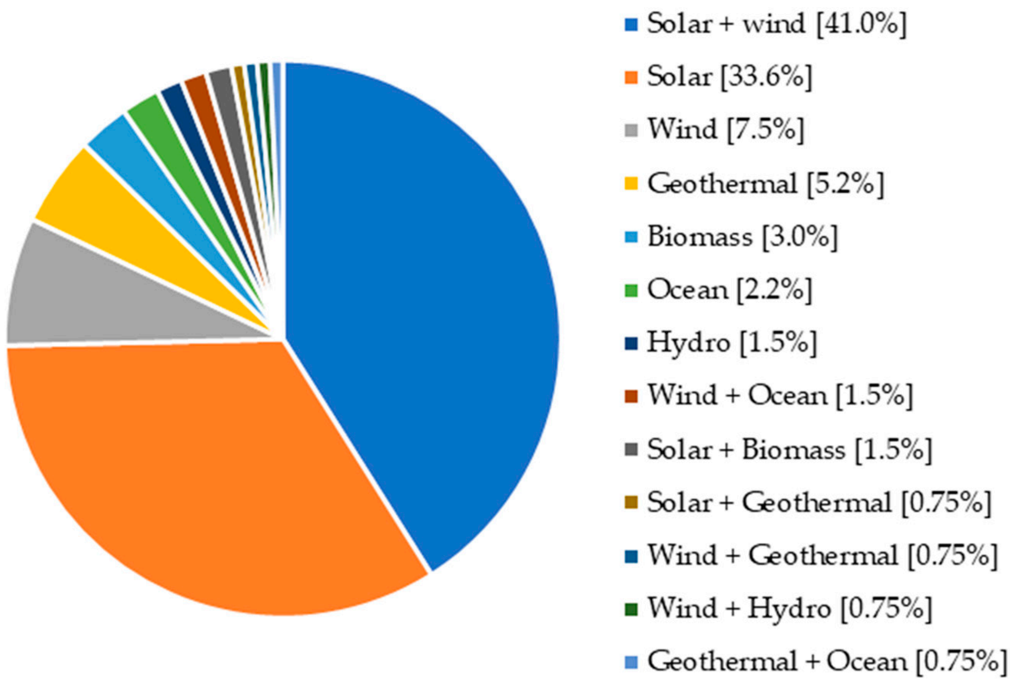

Figure 11. Renewable energy distribution. Data were extracted from Scopus for the period 2009–2022.

These results are in line with studies applied exclusively to renewable technologies. Most research is dominated by hybrid energy technologies, especially in the complementary use of solar and wind energy [164]. On the other hand, solar energy is widely recognized as the most studied renewable energy, due to major advances in its technology and significant cost reductions in recent years. Solar energy is also more available and reliable in water-scarce regions, such as Asia and Africa. Unlike wind power, which can be unpredictable, solar power provides more reliable power generation. In addition, solar farms require less land compared to wind parks.

It is noteworthy to address the matter of desalinated water quality and quantity. Previous research has allocated limited consideration to the quality of the produced water, primarily focusing on meeting specific requirements. Furthermore, previous studies have excluded the assessment of seawater and brine qualities from their optimization models. Nevertheless, due to the inherent relationship between the quantity of desalinated water and operational costs, it was consistently included in the optimization problem as a design specification expressed in hourly or daily terms.

4.3. Trends in the Usage of Optimization Algorithms and Modeling Tools

To find out the number of articles specifically focused only on optimization, a new search was proposed with a focus exclusively on papers applying optimization from an engineering point of view. Thus, the complete search resulted in the following: (TITLE (desalination OR desalting OR desalinization) AND KEY (optimization) AND TITLE-ABS-KEY (renewable AND energy OR energies OR resource)) AND PUBYEAR > 2008 AND PUBYEAR < 2023 AND (LIMIT-TO (DOCTYPE, "ar")) AND (LIMIT-TO (LANGUAGE, "English")) AND OR EXCLUDE (SUBJAREA, "SOCI") OR EXCLUDE (SUBJAREA, "EART")).

The search returned a total of 96 [3,15–20,29–117] articles identifying different optimization methods, computational tools, and the number of criteria used for optimization. The main results are presented in Figures 12–15.

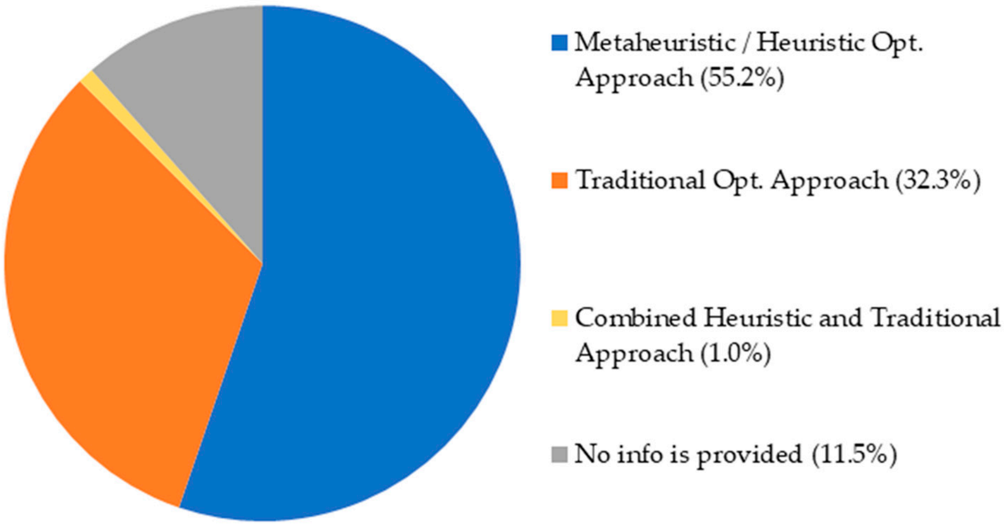

Figure 12. Contribution of the articles employing metaheuristic and exact methods. Data were extracted from Scopus for the period 2009–2022.

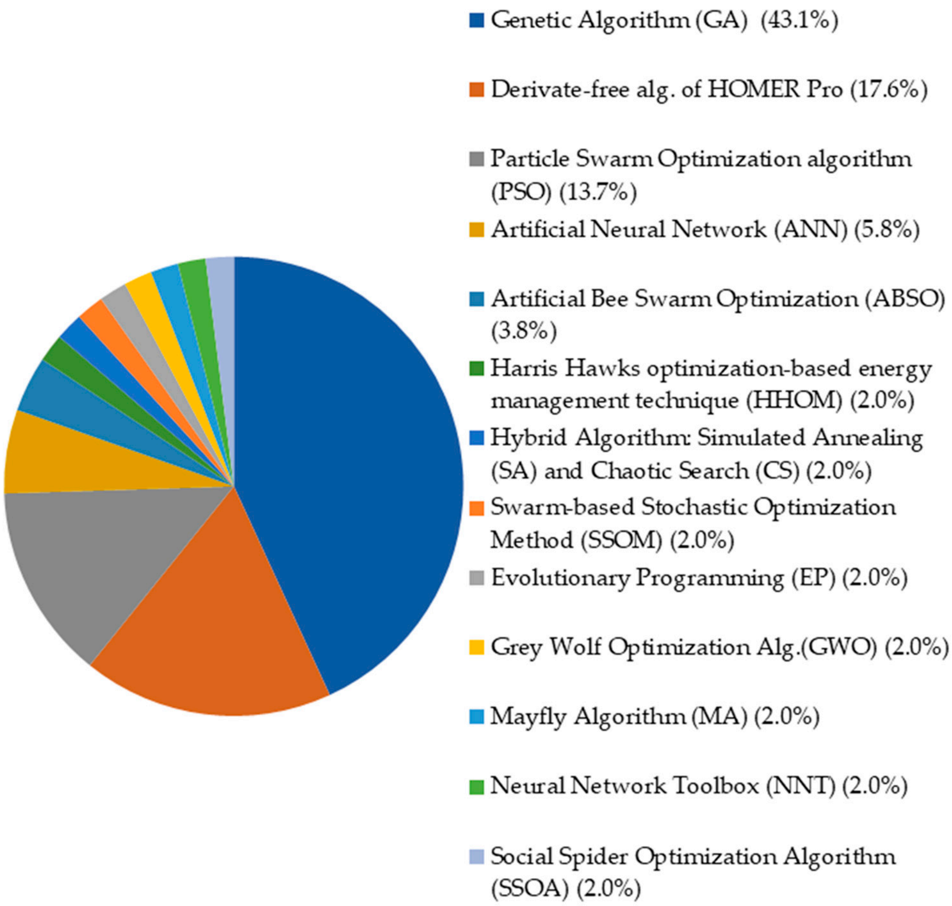

Figure 13. Percentages of distribution of the metaheuristic/heuristic, traditional optimization approaches used in sizing renewable energy systems-based desalination. Data were extracted from Scopus for the period 2009–2022.

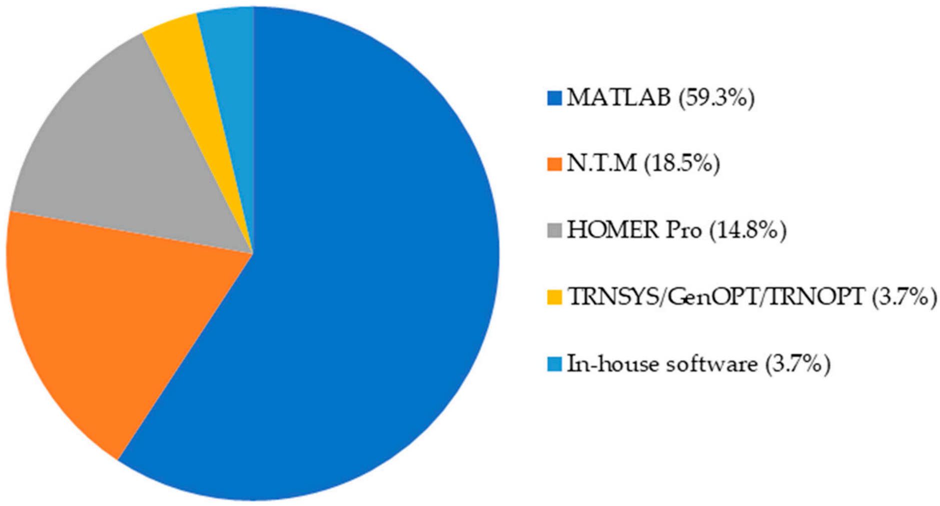

Figure 14. Proportions of the computational tools used for metaheuristic/heuristic optimization approaches in sizing renewable energy systems-based desalination. Data were extracted from Scopus for the period 2009–2022.

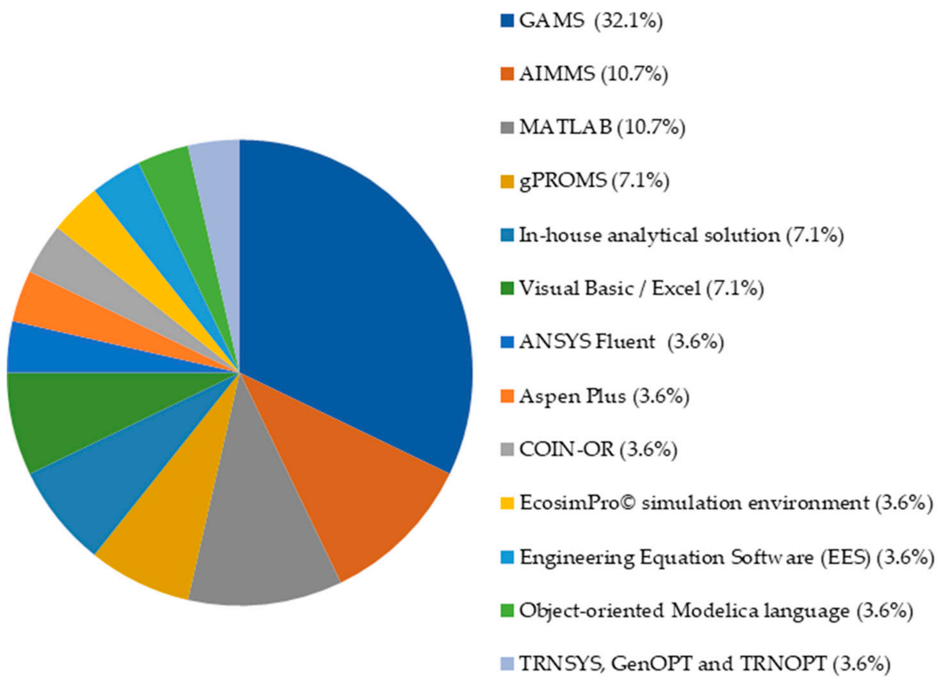

Figure 15. Percentages of distribution of the exact optimization algorithm used in sizing renewable energy systems-based desalination. Data were extracted from Scopus for the period 2009–2022.

Figure 12 illustrates the percentage of articles addressing approximated optimization methods (derivate-free methods, such as metaheuristic/heuristic approaches) and traditional optimization methods (derivate-based methods). It can be observed that from a total of 96, 53 articles correspond to derivative-free methods (55.2%), while 31 articles employ traditional optimization algorithms (32.3%). Moreover, it should be mentioned that in 11 articles, no mention of the type of optimization strategy is reported. Only one article combining metaheuristic/heuristic and traditional optimization approaches was found.

Regarding the application of derivative-free methods, Figure 13 shows that the Genetic Algorithm (GA) is the metaheuristic algorithm most widely used in optimizing RES-powered desalination. It was used in 23 articles, representing 43%, followed by derivate-free algorithms supported by the HOMER Pro simulator, Particle Swarm Optimization (PSO), and Artificial Neural Network (ANN). As shown in Figure 14, the authors widely preferred MATLAB to implement the derivative-free algorithm, mainly the genetic algorithms. From the contributor's perspective, it is possible to identify 48 different first authors. Maleki A. from the University of Tehran, Iran, appeared three times as the first author ([90,92,96]). In addition, from the number of article citations, Maleki et al. have two papers with the highest number of citations: the papers entitled "Design and optimization of autonomous solar-wind-reverse osmosis desalination systems coupling battery and hydrogen energy storage by an improved bee algorithm" published in Desalination (2018) [96] and "Design of a cost-effective wind/photovoltaic/hydrogen energy system for supplying a desalination unit by a heuristic approach," published in Solar Energy (2016) [90], followed by Abdelshafy et al. from Egypt-Japan University of Science and Technology, Egypt with the paper entitled "Optimal design of a grid-connected desalination plant powered by renewable energy resources using a hybrid PSO–GWO approach" published in Energy Conversion and Management (2018), with 128 citations [78].

Regarding the application of traditional optimization methods, as in Figure 15, GAMS software is the computational tool most widely employed to apply the conventional optimization algorithms (branch-and-cut procedure). From the contributor's perspective, it was possible to identify two authors acting as first authors in two or more articles. Okampo from the University of Johannesburg (South Africa) is the first author of all three articles presented by South Africa ([44,61,68]), while Ghaithan A. from the King Fahd University of Petroleum and Minerals in Saudi Arabia is the first author of two articles over a total of three articles presented by this country [33,34].

Finally, it is interesting to mention that from the total of 96 articles, 57 articles addressed single optimization designs (60%), and 39 articles focused on multi-objective optimization designs (40%), considering mainly the minimization of total cost and greenhouse gases emissions or minimization of total cost and maximization of freshwater production.

5. Research Gaps and Future Directions

After analyzing the information from the proposed search method in Section 3, gathered from 139 articles addressing studies of simulation and optimization for RES-DS systems, it is evident that there are various research opportunities worth mentioning. In terms of total article production, only 24.6% of countries worldwide are involved in this specific area, with Iran and China at the top of production with seventeen articles each. This low participation and lack of commitment are worrying, especially considering the current water and energy scarcity many countries face. It is crucial that all countries, particularly those at high risk of such shortages, become more involved. Furthermore, the level of cooperation between countries is low, with the United Kingdom leading the list of countries with the highest number of collaborations (fifteen) established with ten other countries, suggesting that there may be significant room for growth in promoting collaboration and partnership between these nations. Similarly, the level of cooperation and collaboration between different research groups is small, although it is well-known that collaboration can always be productive and beneficial for further progress. In conclusion, all research groups from all countries are invited to deepen their interests in this field and, at the same time, to broaden their contacts with external research groups.

Future directions in the field of renewable energy-driven desalination endeavor to tackle the prevailing challenges and augment the efficacy and viability of these systems. A pivotal focal point lies in the advancement of sophisticated hybrid systems that amalgamate multiple renewable energy sources for desalination purposes. Through the integration of solar, wind, and other renewable energy technologies, these hybrid systems can capitalize on the strengths of each source, optimizing energy generation and mitigating issues pertaining to intermittency. Moreover, there exists a burgeoning interest in exploring nascent renewable energy technologies, such as tidal, wave, and osmotic energy, for their applicability in desalination. These technologies exhibit potential in harnessing the energy present in the ocean and salinity gradients to drive desalination processes. Another significant trajectory entails the utilization of diverse energy storage systems to amass surplus renewable energy and ensure the uninterrupted operation of desalination plants during periods of low energy availability. Progress in energy storage technologies, such as hydrogen batteries and compressed air energy storage, can profoundly bolster the dependability and resilience of renewable energy-powered desalination systems. Nonetheless, despite the lower carbon footprint of renewable energy sources compared to fossil fuels, their implementation can still bear environmental repercussions. The manufacturing and disposal of photovoltaic panels and wind turbine blades, for instance, can generate waste and potential pollutants, necessitating responsible management throughout their life cycle. Additionally, the prudent management of seawater intake and discharge in any desalination process is imperative to avert adverse consequences stemming from high salinity and elevated temperature levels in the discharged brine, which may detrimentally impact marine ecosystems and coastal waters. Furthermore, endeavors are being directed towards optimizing desalination processes through the development of advanced membrane materials, heightened fouling resistance, and enhanced system designs. Regrettably, no articles were discovered that comprehensively address a detailed life cycle analysis (LCA) for the entire renewable energy-powered desalination systems, underscoring its significance as another critical direction for future exploration.

From the viewpoint of simulation and optimization techniques, research trends show that only 96 articles focus on optimizing desalination systems using renewable energies. Among these, 53 articles utilized metaheuristic optimization approaches, while 31 used classical optimization techniques (considering information about the objective function and constraints in the optimization algorithms). However, there is a research gap in the absence of hybrid optimization methodologies that combine both metaheuristic and classical exact optimization methods. This gap should be explored, as the combination of approximate and exact methods can bring significant advantages in problem-solving, for example, using the solution generated by approximate methods, such as initializations and the boundary, for classical methods, thus reducing search gaps. This would allow users to incorporate more details into the optimization models.

The aforementioned future directions collectively establish a foundation for sustainable and resilient water solutions, prompting the need for a comprehensive global perspective and a more realistic approach to research. This approach extends beyond mere cost reduction and encompasses a holistic understanding of the entire system's involvement and its influence on the surrounding environment. It necessitates the consideration of environmental and social impacts, as well as the potential integration of the water–energy nexus, such as the co-production of water and energy. By adopting this broader perspective, a more comprehensive and robust framework can be established for the development and implementation of future water solutions.

6. Conclusions

This study aimed to analyze the research trends, the major contributors, the most used renewable energies, and the simulation/optimization methods and to recommend future directions of study in the integration of desalination with renewable energies approached from numerical simulation/optimization.

In terms of the overall analysis, it is clear that this is a rapidly growing field, as evidenced by the increasing number of published papers and citations. However, there has been limited global implementation, with only 48 countries involved in the research and limited collaboration between them. The United Kingdom has the most collaborations with 15. Additionally, there is a lack of co-participation among different groups of scientists, with 97 clusters of researchers identified without connections between them. This is an area that needs improvement, as collaboration between different research groups could lead to more rapid advancements in the field. Solar and wind energy have been extensively studied, but other renewable energy sources have not been explored as much. In particular, there are significantly fewer articles addressing the optimization of renewable energy-powered desalination systems, with authors primarily using Genetic Algorithms/MATLAB and CPLEX solver/GAMS as optimization algorithms and tools. To gain a better understanding of this field, it would be beneficial to produce a review article that takes into account the mathematical methods used, such as LP, NLP, and MNLP, and provides an in-depth analysis of the mathematical development in terms of its degree of detail, including the treatment of equations and variables.

In the field of RES-DS systems, notable advantages arise with regards to reducing dependence on fossil fuels and mitigating climate change. However, they also exhibit certain limitations, environmental considerations, and practical challenges. The intermittent nature of renewable energy sources poses variability in energy availability for desalination, necessitating solutions, such as water or energy storage, to ensure a consistent and reliable water supply. The implementation of control mechanisms and storage systems to enable the efficient and dependable operation of RES-DS systems remains an area that requires dedicated research efforts.

All desalination systems release warm brine into the ocean, potentially impacting marine ecosystems and local water temperatures. Organisms may suffer harm due to entrapment in intake screens or exposure to high salinity levels in the discharged brine. Financial barriers, such as the installation and setup costs of renewable energy systems, hinder the widespread adoption of desalination technologies based on renewable energy sources. Additionally, RES-DS technologies are still in the developmental or demonstration stages, warranting a thorough evaluation of their scalability and long-term reliability. Advancements in materials, system design, and performance are crucial to facilitate the extensive deployment of RES-DS systems.

Sustained research and development efforts, infrastructure investment, and policy support are imperative to strike a balance between the environmental advantages of renewable energy and the feasibility and practicality of desalination operations.

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