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Desalination processes supported by renewable energy sources managed by artificial intelligence

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ABSTRACT

In recent decades, a growing problem of overexploitation of freshwater resources and lowering the level of ground and surface water has been observed. As a result, approximately 60% of the world's population lived in areas where water was scarce for part of the year. Faced with these challenges, saving water savings and increased water efficiency became a priority, both in urban and agricultural areas. One of the solutions to this problem was water desalination processes, which were considered, however, to be significantly energy-intensive processes. The article described the idea of integrating desalination processes with renewable energy sources and artificial intelligence as a support to optimise the desalination process in technological, economic, and ecological terms. Previous experience in integrating the mentioned technologies was presented, as well as the potential of implementing artificial intelligence and its impact on specific areas of desalination processes, renewable energy sources, environmental, and economic issues, mainly in terms of data collection and analysis as well as predictive and operational monitoring. The use of artificial intelligence to monitor, manage and optimise water desalination processes had the potential to reduce costs and increase efficiency. This was an innovative approach that could help meet the growing demand for clean drinking water in a more sustainable way, while also having a positive impact on the environment.

Keywords: Desalination; Renewable energy sources; Artificial intelligence

1. Introduction

The trend of excessive use of freshwater resources, as well as the decline in the status of ground and surface waters, observed in recent decades, has led to a situation in which around 60% of the global population live in a water basin that encounters water stress for at least part of the year [1]. Access to good quality drinking water is becoming increasingly limited, also in new areas where water supply was not a critical problem [2].

Saving water and increasing the efficiency of its use in technological processes is a challenge for the modern world. This also applies, and perhaps above all, to agricultural areas [3]. One way to solve this problem is through water desalination processes, providing a solution that is somewhat economically viable and technologically feasible [4–8]. There are estimated to be approximately 16,000 water desalination plants located in 177 countries with a total desalination capacity of more than 95 million m^3/d [9], and their number should grow very quickly in the near future [8].

Seawater provides an unlimited source of water for desalination processes. The second potential source is brackish water, that is, in many regions it comes mainly from underground sources. Membrane technologies dominate in desalination processes – 69%–73% of all installed systems in the world [9,10], while thermal techniques account

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for approximately 27% [8,10]. Regardless of the desalination technology, these are highly energy-intensive processes. In this situation, solutions are required to reduce unit costs and improve the economic profitability of such projects. Hybrid systems that combine various desalination techniques and renewable energy sources (RES) seem to offer the most promising solutions in the context of current challenges and future developments [5,11–14]. Taking into account significant trends in action against negative climate change, this approach will play a particularly important role in the future [15–19].

Generally, each of the renewable energy sources (solar energy, wind energy, geothermal energy, water energy, biomass, salinity gradient) can be indicated as potentially possible to use to support desalination processes. However, there are technologies that dominate in terms of popularity of application: solar and wind energy, as well as various variants of their hybrid systems in cooperation with energy storage [20]. This is due to the availability of the mentioned energy sources and the technical possibilities of their relatively easy and quick implementation and the execution of the investment process. Of course, the appropriateness of use will be determined by a number of conditions, which artificial intelligence can help assess.

The article combines several threads that, according to the authors, will determine trends and megatrends in the water-energy-climate nexus (Fig. 1). This is access to freshwater resources, access to stable and cheap energy and limiting the negative impact on the quality of the natural environment.

Regarding future prospects, it seems that the development directions indicated above, observed over recent years, will continue to ensure sustainable exploitation of renewable energy sources and water resources, mainly in regions with high water scarcity [21]. There is also a visible need to use renewable energy sources that are characterised by stable and continuous energy production, such as geothermal energy [22]. Artificial intelligence (AI) can play an important role in optimising and improving the desalination process, including processes powered by renewable energy sources. This is a natural conclusion resulting from the research and use of AI in the management and optimization of energy processes, as well as energy-intensive processes, and desalination and water treatment technologies are considered such.

Fig. 1. The idea of synergy of demand for water, energy and impact on the natural environment.

So far, desalination has been mainly combined with renewable energy sources or/and energy storage. However, analysis of previous research leads to the conclusion that artificial intelligence has been relatively rarely included in these issues. Consciously or unconsciously, considering that at some level of generalisation, artificial intelligence accompanies most technological processes due to the data collection and analysis process. This idea originated from the management of energy processes and the need to increase their efficiency in terms of achieving economic and, indirectly, ecological effects. This issue was presented in an interesting and comprehensive way by Ahmad et al. [10]. As the authors claim, the energy industry stood at a crossroads where digital technological advancements had the potential to revolutionise energy supply, trade, and consumption. They proposed a new digitalization model was powered by artificial intelligence (AI) technology, allowing autonomous control of energy supply, demand, and renewable sources in the power grid. The study by Ahmad et al. [10] focused on the past use of AI techniques in the energy sector, outlining its role in solar and hydrogen power generation, supply and demand management, and recent AI advancements. The findings demonstrated how AI outperformed traditional models in controllability, big data handling, cybersecurity, energy efficiency optimisation, and predictive maintenance control.

Without a doubt, AI technologies can support the energy industry in taking advantage of the growing opportunities associated with the adoption of the Internet of Things (IoT) and the integration of renewable energy sources, as confirmed, among others, Kow et al. [23] and Sodhro et al. [24]. Moreover, predictive technologies are well known and widely used in forecasting the acquisition and conversion of energy resources, including forecasting energy demand and changes in energy prices on the market [25]. This, in turn, allows to be optimistic about their implementation in innovative and modern technological processes. Recent years have seen the improvement of the use of AI in planning and forecasting energy demand, including energy from renewable energy sources [26–28]. In summary, AI plays an important role in the energy sector, addressing challenges such as big data management, advances in deep learning and machine learning, smart robotics, IoT integration, cybersecurity, and computational power. Advances in AI can help optimise the power grid, enhance resilience, and maintain reliability. It must be remembered that the goal is to maximise AI's benefits while minimizing potential harms and risks in the energy sector.

The aim of the article is to indicate the potential of hybrid cooperation between desalination technologies, the use of renewable energy sources and artificial intelligence in an orderly manner. This allows understanding the broader context in an innovative approach to water-energy-climate issues. As well as setting the direction for further research.

2. Review of previous research

The research conducted so far indicates that the idea presented is, firstly, an innovative approach, and secondly, an interdisciplinary one. Sayed et al. [29] reviewed the literature in this area, who point out that the design of

RES-powered desalination systems is hampered by unpredictable energy demand and RES intermittency. The use of intelligent techniques such as AI is key to finding optimal solutions. At the same time, however, attention is drawn to two issues, namely the fact that hybrid systems constitute a more comprehensive solution and the need to take into account the issue of energy storage in this type of energy systems. The idea of combining the desalination process using renewable sources and energy storage in the artificial intelligence is presented in Fig. 2.

The use of AI systems in modelling desalination systems with RES has primarily been conducted with reference to the utilisation of solar thermal technology in solar still desalination. Santos et al. (2012) [30] predicted solar still distillate production using artificial neural networks (ANN) and local weather data from two commercial solar stills that were operated for 1.5 y. The study found that 31%–78% of the predictions of the ANN model were within 10% of actual yields, and 93% to 97% of the variance was accounted for by the ANN model. With half to two-thirds of the input data, at least 60% of model predictions closely matched actual yields, suggesting the ANN method could have been used to predict other solar still designs in various climates.

Mashaly et al. [31] developed a mathematical model to forecast solar still performance under hyper-arid conditions using the artificial neural network technique. The model required ten input parameters, including weather variables and water properties. It was trained, tested, and validated with measured data, demonstrating high coefficients of determination (ranging from 0.991 to 0.99) and low errors (average RMSE of 0.04 $L/m^2\cdot h$) for predicting water productivity, operational recovery ratio, and thermal efficiency. The findings indicated that the model was effective and accurate in predicting solar still performance with minimal errors. Furthermore, Mashaly et al. [32] study aimed to assess the feasibility of modelling the instantaneous thermal efficiency (gith) of a solar still using multi-layer perceptron (MLP) neural networks and multiple linear regressions (MLR) based on weather and operational data. In both models nine input parameters were used, including weather variables and water properties. Performance evaluation criteria indicated that the MLP model outperformed the MLR model, with a higher coefficient of determination and a lower root mean square error, making it the preferred choice for precise geographic prediction in the design of solar desalination systems. In a study by Mashaly and Alazba [33], an ANN model was developed to predict the thermal performance (instantaneous thermal efficiency – ITE) of an inclined passive solar still in an arid climate using agricultural drainage water (AWD) as the feed source. Meteorological and operational variables were used as input, and the optimal ANN model had a root mean square error (RMSE) of 1.933% and a mean coefficient of determination (CD) of 0.949. In comparison, a multiple linear regression model (MLR) performed less accurately, with a mean RMSE of 4.345% and a mean CD of 0.739, highlighting the superior performance of the ANN model.

Essa et al. [34] developed a new productivity prediction model for active solar stills, enhancing traditional artificial neural networks with the Harris Hawks Optimizer. The model, known as Harris Hawks Optimizer, an artificial neural network, outperformed two other models and matched well with experimental data for three distillation

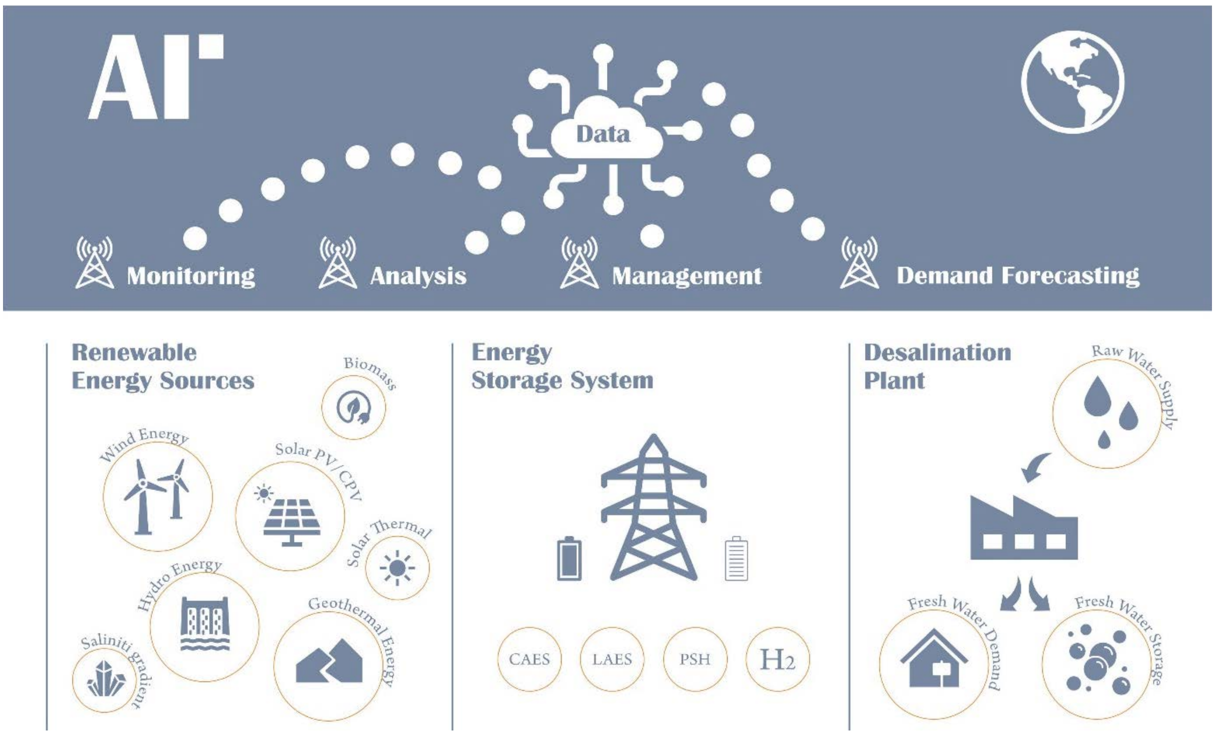

Fig. 2. The idea of combining the desalination process using renewable sources and energy storage in a process managed by artificial intelligence.

systems, indicating its superior accuracy in predicting solar still yield. Salem et al. [35] utilised an artificial intelligent regression model to predict the efficiency of water desalination with solar thermal energy. It helped manufacturers and researchers evaluate the productivity of the system before implementation. Multiple regression algorithms, including OMLP (optimised multilayer perceptron), were compared, with OMLP demonstrating superior performance in predicting key variables related to the efficiency of the desalination system. Finally, Salem et al. [36] research focused on solar-driven steam materials and desalination systems, offering a sustainable solution in water-scarce areas with abundant solar energy. Artificial intelligence (AI), including Explainable AI (XAI), was increasingly employed to enhance desalination processes. The study introduced an XAI-DL model based on deep learning, achieving an accuracy of 82.64% in predicting cooling quality and providing interpretable insights for decision making.

Another main area of interest in the context of published research results is solar energy using photovoltaics and wind energy. Several schemes have been proposed by Porrazzo et al. [37] to couple desalination processes with the use of RES, but faced challenges due to the intermittent nature of the energy source. In this study, a solar-powered membrane distillation system was used to develop and test an optimised control strategy. An ANN model was trained using experimental data and used to analyse system performance under various operating conditions, leading to the development, implementation, and testing of a control system to optimise distillate production in varying conditions. In the study of Lee et al. [38], a novel productivity prediction model for an active solar still was developed, aiming to enhance the performance of traditional artificial neural networks using the Harris Hawks Optimizer. The proposed model was compared with two other models: the support vector machine and traditional artificial neural network, with a focus on the experimental behaviour of the solar still. Models were applied to predict the yield of three distinct distillation systems, resulting in a significant 53.21% productivity increase for the active distiller integrated with a condenser at a fan speed of 1350 rpm. The models' performance was assessed using various statistical criteria, where the Harris Hawks Optimizer – artificial neural network exhibited the highest accuracy in predicting solar still yield compared to real experimental results.

Wind energy to supply reverse osmosis desalination plant was studied by Cabrera et al. [39]. In this paper, two studies were conducted on the performance simulation and analysis of a prototype wind powered seawater reverse osmosis (SWRO) desalination plant installed on Gran Canaria island. Three machine learning techniques (artificial neural networks, support vector machines, and random forests) were implemented to predict the plant's performance. The results showed that support vector machines and random forests were significantly better predictors of the plant performance than neural networks, and the operating mode with variable pressure and flow rate operated more continuously but produced slightly less permeate with higher conductivity over a year.

The natural direction in the development of the use of renewable energy in desalination processes is the construction of hybrid systems. It is also noticeable in published research.

Al-Alawi et al. [40] discussed the development of a predictive ANN-based controller for the optimum operation of an integrated hybrid renewable energy-based water and power supply system (IRWPSS). The integrated system included photovoltaic modules, a diesel generator, a battery bank for energy storage, and a reverse osmosis desalination unit. The ANN-based controller was designed to make decisions about the power supply status of the diesel generator, maintain a minimum loading level on the generator during specific conditions, and reduce fuel dependence, engine wear, and greenhouse gas emissions. The study results indicated that the ANN model could accurately predict power usage and generator status.

PV-Wind hybrid systems with energy storage to power the RO process were conducted by Li et al. [41]. This research aimed to design a sustainable and reliable hybrid renewable energy system (HRES) coupled with a RO desalination system (HRES-RO) to address energy and sustainability challenges in remote areas. Future energy supply and water demand were forecasted using recurrent neural networks, and multi-criteria optimisation was performed to minimize annual costs and greenhouse gas emissions. The results showed that the proposed framework optimised the HRES installation and reduced the potential loss of power supply probability by 18.3%, highlighting the benefits of advanced forecasting algorithms in addressing future uncertainties. In the paper by Charrouf et al. [42], an ANN power management system for a reverse osmosis desalination unit, fueled by hybrid renewable energy sources such as solar PV and a wind turbine with a battery bank for energy storage, was studied. The ANN power management system aimed to ensure the smooth transfer of power generated by these sources, considering the variability in wind speed and solar irradiation over a 24-h operation and the constraints of the RO unit and water demand. The study involved designing, modelling, and implementing control strategies for all system components, and the ability of the results demonstrated the ANN power manager to define operating modes based on the proposed flowchart.

Hybrid systems were also analysed in the context of probably the most popular desalination method, reverse osmosis. In the work presented below, the issue of energy storage was also taken into account. Bourouni et al. [43] presented a new model based on genetic algorithms to optimize small RO units coupled with RES, with a focus on hybrid systems (PV/WIND/batteries/RO). The objective function was to minimize the total water cost, which included capital and operating expenses. The paper also included a case study of a PV/RO unit installed in Ksar Ghilène village in southern Tunisia in 2007, providing practical insight into the discussed concepts. Maleki et al. [44] investigated a hybrid photovoltaic/wind/hydrogen/reverse osmosis desalination system designed for a standalone region in Iran, with a focus on increasing freshwater availability and meeting load demand. The configuration of the hybrid system was optimised on two criteria: life cycle cost and power supply reliability. Using artificial bee swarm optimisation, the results indicated that the photovoltaic, hydrogen, reverse osmosis desalination system was the most cost-effective energy solution, followed by photovoltaic, wind, hydrogen, reverse osmosis desalination and wind, hydrogen, reverse osmosis desalination systems. Abdelshafy et al. [45] presented a grid-connected hybrid renewable energy system integrated with a reverse osmosis desalination plant designed to supply freshwater to a residential community. It employed photovoltaic modules and wind turbines as primary energy sources, with energy storage options that included battery and hydrogen storage, along with a backup diesel generator. A novel multiobjective optimization method, was used to determine the optimal component sizes for minimising both the total cost of freshwater production and CO_2 emissions over a 20-y period. MATLAB software was used for weather data analysis, energy management strategies, and optimisation modeling. Furthermore, sensitivity analyses indicated that variations in annual solar irradiance had a more substantial impact on total investment costs compared to wind speed fluctuations.

Maleki [46] presented a grid-connected hybrid renewable energy system that incorporates a reverse osmosis desalination plant for residential freshwater supply. The system combined photovoltaic and wind power with battery or hydrogen storage, along with a backup diesel generator. A novel multi-objective PSO-GWO optimisation method was applied to determine optimal component sizes, minimising costs and CO_2 emissions over a 20-y period. The results favoured the PSO-GWO hybrid approach, and the sensitivity analysis highlighted the impact of annual variations in solar irradiance on investment costs. Zhang et al. [47] optimised a hybrid reverse osmosis desalination system powered by solar and wind energy for self-sufficient regions. Three hybrid configurations were investigated: solar-wind-battery-RO desalination, solar-battery-RO desalination, and wind-battery-RO desalination. An optimization model aimed to minimize the life cycle cost and ensure reliability using the probability of power interruptions. The developed hybrid search algorithm outperformed simulated annealing and chaotic search, leading to cost savings and improved reliability for freshwater supply and meeting electricity demand in autonomous regions. Finally, Li et al. [41] designed a hybrid renewable energy system (HRES) integrated with reverse osmosis desalination to accommodate variable energy supply and fluctuating water demand. It employed recurrent neural networks for forecasting energy supply and water demand and applied multi-criteria optimisation to minimize costs and greenhouse gas emissions. The proposed HRES reduced the potential loss of probability of power supply by 18.3% compared to the baseline, underscoring the value of advanced forecasting techniques in managing future energy uncertainties.

In the case of other renewable energy sources, such as geothermal energy, hydropower or biomass, AI can be used in the context of optimising the use of resources. However, this is an unpopular issue, but it certainly has scientific potential for the future.

3. Determining the function of RES + AI in desalination systems

Artificial intelligence can be used in several ways to increase the efficiency, sustainability and profitability of desalination processes that involve the use of renewable energy sources, as shown in Tables 1 and 2. The general idea of organising the processes that artificial intelligence can manage was to assign one of the basic activities to AI, which includes predictive monitoring, operational monitoring and data analysis. In the case of predictive monitoring, management and optimisation of treated water production were indicated, where the role of AI is to monitor the operational parameters of the desalination installation, manage water resources and monitor treated and treated water (raw water). In the case of operational monitoring and data analysis, predictive forecasting of energy production (use of historical data and meteorological forecasts), analysis of real-time data on energy consumption and weather conditions, as well as the use of intelligent energy microgrids, were indicated.

The impact of artificial intelligence on the desalination process, on the energy system based on renewable energy sources, and on the natural environment was determined. The economic aspect was generally defined as determined by all the above-mentioned components and described as a general reduction in operating costs resulting from optimization of the operation of desalination systems and a hybrid energy source based on renewable energy sources, despite the increase in investment costs.

Desalination processes have a significant impact on aspects such as equipment failure prediction and prevention, pre-failure planning and maintenance, reduction of downtime and maintenance costs, membrane fouling control and forecast, pressure and flow control, analysis of a wide range of data (meteorological, availability of raw water, resilience to climate change) and demand forecasts, to optimise the integration of desalinated water into the overall water supply and distribution network, raw water quality, adaptation of the desalination process to maintain consistent treated water quality standards, optimisation of the desalination process, including the selection of optimal feed water flow rates, pressures, and the use of pre-treatment techniques, as well as maximising water recovery by adjusting the desalination process parameters and reducing the amount of brine waste generated. These are only the aspects resulting from predictive monitoring. In the case of operational monitoring and data analysis, the following can be distinguished: ensuring continuity of energy supplies to the desalination system, planning production in relation to the RES energy availability profile, optimising energy consumption, ensuring continuity of energy supplies to the desalination system, flexibility of the technological system, ensuring continuity of energy supplies to the desalination system, scalability in relation to energy supply to the desalination system, planning of energy production to the parameters of charging/discharging the energy storage.

Analogous functions and effects of AI were assigned to renewable energy sources, where at the predictive monitoring stage the electricity consumption through the data monitoring and management system, the adaptation of desalinated water production to the changing availability of renewable energy through the storage of treated water and the indirect impact in the use process were distinguished. brine waste as thermal energy storage in liquid salt, and increasing energy efficiency using CSP systems. Operational monitoring and data analysis included ensuring complementarity of

Table 1
Possibilities of using AI in desalination processes supported by renewable energy sources in the predictive monitoring stage

	Action	Role of the AI	Impact on desalination processes	Impact on renewable energy sources		Economical aspects		Impact on the natural environment
Predictive monitoring	Management and optimisation of treated water production	monitoring of the operational parameters of the desalination plant	predicting and preventing equipment failures planning and maintenance before failure occurs reduction of downtime and maintenance costs control and prediction of membrane contamination pressure and flow control	electricity consumption by the monitoring and data management system	>	general reduction in operating costs resulting from optimisation of the operation of desalination systems and a hybrid energy source based on renewable energy sources, despite the increase in investment costs	<	reducing the impact of uncontrolled technological failures and their negative impact on the local ecosystem
		water resources management	analysis of a wide range of data (meteorological, raw water availability, climate change resilience) and demand forecasts, in order to optimise the integration of desalinated water into the general water supply and distribution network	adapting the production of desalinated water to the changing availability of renewable energy by storing treated water				reducing pressure on drinking water sources
		monitoring the quality of treated and treated water	raw water quality adapting the desalination process to maintain consistent treated water quality standards optimisation of the desalination process, including the selection of optimal feed water flow rates, pressure and the use of pre-treatment techniques maximising water recovery by adjusting the parameters of the desalination process and reducing the amount of brine waste generated	indirectly in the process of using brine waste as thermal energy storage in liquid salt, and increasing energy efficiency using CSP systems				reducing pressure on raw water sources and reducing brine storage and disposal processes

electricity production, coordinating the operation of hybrid energy systems, reducing the need to use conventional backup generators or grid electricity, adapting to changing meteorological conditions, minimising energy consumption, planned downtime (e.g., need for maintenance), increasing the total efficiency of the use of generated energy in real time, managing priorities.

Ecological function and impact on the natural environment are an indispensable element of every technological process, especially processes characterised by high energy consumption. The need to conduct environmental life cycle assessment studies in a way that is complementary to changing operating conditions of installations over time is a challenge. However, at the same time, it is an activity that

Table 2
Possibilities of using AI in desalination processes supported by renewable energy sources at the stage of operational monitoring and data analysis

	Action	Role of the AI	Impact on desalination processes	Impact on renewable energy sources		Economical aspects		Impact on the natural environment
Operational monitoring/data analysis	Management and optimization of energy generation and consumption	predictive forecasting of energy generation (using historical data and meteorological forecasts)	ensuring continuity of energy supply to the desalination system	ensuring complementarity of electricity production	>	general reduction in operating costs resulting from optimisation of the operation of desalination systems and a hybrid energy source based on renewable energy sources, despite the increase in investment costs	<	reducing the consumption of conventional energy carriers and limiting the emissions of conventional fuel combustion products into the natural environment
			production planning in relation to the RES energy availability profile	coordinating the operation of hybrid energy systems				
			optimizing energy consumption	reducing the need for conventional backup generators or grid electricity				
		real-time data analysis of energy consumption and weather conditions	ensuring continuity of energy supply to the desalination system	adaptation to changing meteorological conditions				
			flexibility of the technological system	minimizing energy consumption				
	Management and optimization of energy storage	the use of intelligent energy microgrids	ensuring continuity of energy supply to the desalination system	planned downtime (e.g., maintenance required)	>		<	supporting the management of energy raw materials resources
			scalability in relation to energy supply to the desalination system	increasing the total efficiency of the use of generated energy in real time				
			planning energy production to the parameters of charging/discharging the energy storage	priority management				

opens up a number of possibilities to improve the technological processes being implemented, in this case desalination. The impact of AI, independent of LCA, was defined in terms of reducing the impact of uncontrolled technological failures and their negative impact on the local ecosystem, reducing pressure on drinking water sources, reducing pressure on raw water sources, and reducing brine storage and disposal processes, reducing conventional energy carriers and reducing emissions of conventional fuel combustion products into the natural environment, as well as supporting the management of energy raw material resources.

4. Summary and conclusions

Incorporating artificial intelligence into desalination processes can lead to more efficient and sustainable water production, making desalination a more viable solution to water scarcity in regions with limited freshwater resources. However, the integration of artificial intelligence in desalination processes combined with renewable energy sources provides an almost comprehensive solution, for which the missing element is energy storage. Together, this cooperation can lead to more sustainable and environmentally friendly water production. In particular, one can point to:

- Use of AI for predictive and operational monitoring, which allows for optimisation of treated water production, management of water resources, and monitoring of water quality.
- Predictive forecasting of energy production, analysis of real-time data on energy consumption and weather conditions, and the use of intelligent energy microgrids.
- Optimisation of the operation of desalination systems and hybrid energy systems based on renewable energy sources, leading to reduced operating costs.
- Monitoring of desalination process parameters, water resources management, pressure and flow control, and analysis of a wide range of data to optimise the production of treated water.
- Reducing downtime and maintenance costs, preventing equipment failures, and adapting to changing meteorological conditions in renewable energy production.

- Reduce emissions of conventional fuel combustion products into the natural environment and support the management of energy resources.
- Overall, the use of artificial intelligence in desalination processes and energy production from renewable sources brings economic and ecological benefits and improves sustainable development, positively affecting the quality of life and the natural environment.

Further research and development (R&D) work may focus on developing and implementing advanced technologies based on artificial intelligence (AI) in desalination processes using renewable energy sources. It is crucial to focus research on the development of more advanced algorithms and AI models to monitor and managing desalination processes and energy production from renewable sources. This may include more advanced machine learning and deep learning techniques. Integration of multiple renewable energy sources is another issue on which research should focus. However, it is not cooperation itself that is crucial, but optimization of the operation of these sources in real time and adaptation to changing weather conditions. To make this possible, it is necessary to develop energy storage technologies, including research on new energy storage technologies.

Optimisation of the desalination technology will play an significant role in this process. Research efforts can focus on developing more effective and efficient desalination processes based on data and AI support. This can help reduce costs and increase efficiency. Research on the impact of desalination and energy production processes on the natural environment and on solutions to minimise the negative impact, such as reduction and optimal use of brine, is also necessary. However, progress will only be possible if AI is used in scalable projects. Supporting such research projects can contribute to the further development and implementation of advanced AI-based solutions that will bring economic, ecological and social benefits in the field of water desalination and energy production.

CRediT authorship contribution statement

Conceptualisation: M. Kaczmarczyk, B. Tomaszewska; Writing-original draft preparation: M. Kaczmarczyk, B. Tomaszewska; Writing-review and editing: M. Kaczmarczyk, B. Tomaszewska; Visualization: M. Kaczmarczyk; Supervision: B. Tomaszewska; Project administration: B. Tomaszewska.

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Conflicts of interest

The author declare no conflict of interest. The funders had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript, or in the decision to publish the results.

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