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Forecast the artificial intelligence abetted desalination process with the aid of patent landscape analysis – a teeny review

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ABSTRACT

Desalination a primary technique to overcome the issue of water scarcity is currently the focus of the research community. One of the challenging issues faced concerning the basic needs of mankind is water scarcity and the world can never say no to water, as it is an elixir of life. South Africa's "Day Zero" insists on the need for water preservation as well as the effective utilization of water. Reduction of wastage though serves as one of the ways to overcome the water scarcity, the generation of water effectively from the enormous saltwater available is the ultimate choice. The researcher's focus is currently on improving the efficiency of desalination and hence the conversion rate. This proposed analysis focuses on consolidating the existing artificial intelligence based desalination techniques as well as forecasting the significance and outcome of those techniques with the aid of patent landscape analysis, which proves to be the novel part of this article as well.

Keywords: Artificial intelligence (AI); Landscape analysis; Desalination

1. Introduction

The necessity of water is always in the demanding phase and that affects many countries worldwide. The "Water World" magazine provides the fact that the scarcity in the Middle East doubles in the year 2040 and a few parts of the US and China also get affected by water scarcity [1]. Maybe the reason behind the scarcity is varied we need a common solution to over this. Table 1 provides us multi-variate conclusion that the demand since 2030 will be an alarming factor amidst a negligible change in supply and increase of population in the specific region of the Middle East.

The scenario of water demand in the Middle East urged to take steps on investing fuel in the desalination process, wherein fuel is their major resource. Sustainable development is instituted as a part of that, harvesting the freshwater for a better life is incorporated [3] (Table 2).

It is a well-known fact that even though a major portion of the world is covered by water bodies, a comparatively less percentage is freshwater. The increase in demand for water across the world drives them to involve in the desalination process. From Fig. 1 it is found that among various countries across the world involved in the desalination process, the Middle East remains the major contributor. Also, it is evident that the interest and involvement of the nations across the world in the process of desalination, insists researchers work towards the analysis of desalination techniques. Finally ends up in optimization of the desalination process, which is achieved with the assistance of AI techniques. The following section of the article is aimed at providing insight into the future of desalination by elaborating on various AI-based desalination techniques.

2. AI techniques for desalination

The volume of data and uncertainty of parameters for desalination make the involvement of AI techniques to a greater extent. Among the various desalination models,

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the following four models with a primary focus on AI namely the hydrate model, sustainability optimization model, reverse osmosis model, and graphene nanopore are predominant.

2.1. Hydrate model

The two adaptive intelligence models that are based on an adaptive-network-based fuzzy inference system (ANFIS) along with support vector machine (SVM) techniques are established to effectively predict the desalination efficiency of water produced by a hydrate-based desalination treatment process. For determining the optimal values of SVM sample coefficients, a genetic algorithm is used for evolutionary optimization. The compressed natural gas and CO_2 hydrate generation tests were carried out and the desalination capacity of the produced water was measured and used for sample training and verification. On the completion of model development, graphical and statistical analysis approaches have been used to evaluate the performance of the recommended samples by comparing the sample predictions with the measured test data. For the ANFIS model, the coefficient of determination (R^2) along with the average absolute relative error (AARE) has been calculated as 0.9927 and 0.58% correspondingly, and for the SVM model, the values obtained are 0.9985 and 0.35% correspondingly. These statistical factors confirm the best accuracy along with the robustness of intelligent simulations and hence help in envisaging the desalination performance of water produced by a hydrate-based desalination treatment process. Furthermore, the influence of this statistical technique has been adopted to define the outline. The results obtained show that all test data are reliable and both ANFIS and SVM models are statistically valid [5].

Table 1
Prediction of water demand up to 2050 in the Kingdom of Saudi Arabia [2]

Countries	Population × 10^6	Water production (m^3/d) × 10^6		Year
		Demand	Supply	
Kingdom of	20	4	6	2000
Saudi Arabia	27.5	7.5	12	2010
	32	12	16	2020
	37	19.5	17	2030
	41	29	17	2040
	44	41	17	2050

Table 2
Worldwide contribution in desalination [4]

S. No.	Country	In percentage
1.	Kingdom of Saudi Arabia	18
2.	USA	17.8
3.	United Arabic Emirates	16.66
4.	Spain	7.64
5.	Kuwait	6.46
6.	Qatar	3.39
7.	Oman	1.38
8	Bahrain	1.32
9.	Others	27.35

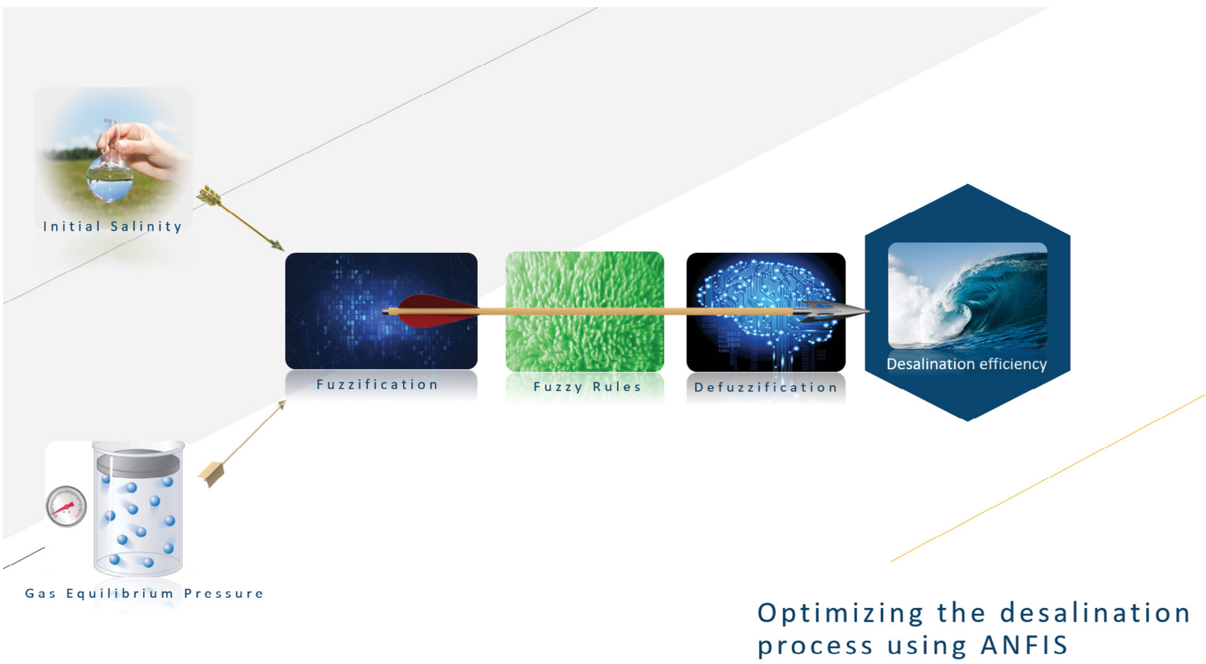

Fig. 1. Optimising the desalination process using ANFIS [5].

ANFIS along with the SVM techniques were first used to model the hydrate-based desalination process. The desalination efficiency is predicted by taking the initial salinity of the produced water and the gas hydrate equilibrium pressure as input parameters. To create the mock-up structure, the hydrate pre-test method is used to measure the desalination capacity of various salinized water in the presence of CNG as well as CO_2. The genetic algorithm is used as an evolutionary optimization technique to obtain adjustable parameters of the SVM model. The reliability of the proposed models is evaluated by comparing the sample predictions with the measured test data and by the calculation of statistical parameters including such as MSE, AARE as well as R^2. The MSE and AARE of the ANFIS model are found to have the desalination competence of 0.2412 and 0.58%, correspondingly, with a high value of R^2 as 0.9927. The values of AARE, MSE, and R^2 for the SVM technique were found to be 0.35%, 0.0843, and 0.9985 correspondingly. These statistical criteria depict the ideal agreement of ANFIS along with the SVM sample forecasts with test data. Tough the SVM method is found to be moderately better than the ANFIS technique, both the proposed intelligent models can be used with greater accuracy to simulate the hydrate-based desalination process. Further, external analysis is done based on the alien technique to assess the accuracy of the implemented data. The results found reveal that all the measured data are reliable as well as that both developed models are statistically correct and acceptable [5].

2.2. Sustainability optimization model

Currently, water desalination has been on the upswing worldwide. The factors such as planning and technical decisions have better significance for the strategic systems, where many plants have been contracted constantly. The divergent desalination combinations based on multiple performance metrics applied over factors such as locations, capabilities, and energy sources were analyzed using AI techniques and proposed for decision-makers to make wise investments. Thus, determining the location of optimal stations and the efficiency of the water desalination system for future expectations. Even further smart results choose a few existing and recommended planting optimal desalination technologies. In addition, a forum for decision-makers that could help in configuring the pipe network and moving water between planting sites is provided by AI techniques. The work proposed is a better way to escalate the strategic decision-making process for the finest water desalination facility. The system proposes a set of AI replacements for numerous desalination plants. The alternative solutions are provided by the decision support systems and tools, but they are incomplete. Hence the proposed work also provides a systematic decision-making process to validate multiple water desalination alternatives, considering the intelligent water pumping network and the pumping of water through each location. The case study of Jordan which is a starting country in desalination is tested with the projected work and the results illustrate where economic and environmental benefits occur and demonstrate how AI techniques can provide the optimal settings for the desalination process to decision-makers.

Jordan's case study is found to have used several AI techniques for decision making in the strategic planning of desalination facilities and a significant factor in environmental considerations is highlighted. Further, an algorithm to improve the desalination process is projected and used to clarify Jordan's case study. The projected method could enable smart sustainable and financial development for desalination installation with the help of AI techniques, by decision-makers and individuals in Jordan. The proposed system hence also offers a better solution to the issue of water scarcity in Jordan, which exploits excess wastewater to produce efficient planting methods [6]. It is shown in the Fig. 2.

2.3. Reverse osmosis model

The process of desalination of salty water and seawater is found to be the main source of the countries that suffer from scarcity of rainwater and are destitute of rivers and lakes. Removal of saltwater is done using a variety of techniques like multi-stage flash filtration, reverse osmosis, membrane filtration, electrolysis reversal, solar evaporation, and so on. The very popular technique is reverse osmosis (RO) as it has a simpler design and is economical due to factors such as low energy, low operating temperature, and low water production costs. AI techniques like artificial neural networks (ANN), as well as support vector regression (SVR), are used for reverse osmosis dewatering. The input parameters of the samples include sodium chloride concentration, feed temperature as well as pressure. The output parameter is the

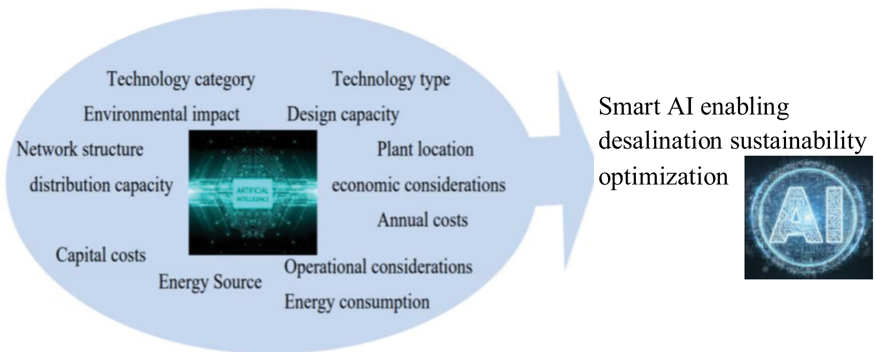

Fig. 2. Proposed idea of using AI for desalination [6].

penetration rate. The experimental data are assessed and verified against AI-based models. These AI-centred models are further equated with the extensively utilized multiple linear regression (MLR) over the virgin test (unseen) dataset based on statistical measures like AARE, R^2, coefficient of determination, and so on. The SVR-based model demonstrates a low value of AARE of 1.95% along with a value of high R^2 of 0.9963 while its corresponding values for ANN and MLR models are 9.35%, 52.04%, 0.9899, and 0.9157 correspondingly. Thus, the structural risk minimization (SRM) principle-based SVR model is found to be the best, most accurate, and generalized in comparison to the empirical risk minimization (ERM) based MLR and ANN models for the saturate rate prediction. Furthermore, through these AI techniques, exceptional predictions can be made for the unseen data which not only diminishes the number of experimentations to be done but also aid the more effective design as well as fabrication of membrane-based desalination unit [7].

2.4. Graphene nanopore

Nanoporous graphene has proven to be a strong candidate for water desalination applications. Its ultrathin thickness makes energy-efficient water desalination possible. The geometry of the hole on the graphene membrane plays a significant role in its dewatering performance. In this work, the nanopore geometry optimization method for graphene membrane using deep reinforcement learning (DRL) was proposed. The nanopore designed using DRL resembles the Osirk Lake fractal shape located in Missouri, which enables significant ion rejection while allowing maximum penetration. The DRL-designed ossicle-shaped hole is shown to have a 10% higher ion rejection rate compared to circular holes while allowing the same amount of water flow. The reason for the high ionic rejection of the Oscar-shaped graphene nanopores is that their shape limits the passage of hydrated ions in certain areas within the hole [8].

The desalination process discussed above is powered by AI techniques and the Table 3 gives the summarization of the outcomes achieved by applying AI to the above desalination process.

From the summarization provided in Table 3, better results for the desalination process are achieved using machine learning, neural networks, and fuzzy logic. The efficiency is improved in terms of power saving, wastage minimization, prediction, etc., and various AI-related techniques that could benefit are identified namely ANN, Fuzzy, Fuzzy reinforcement learning, etc. Fig. 3 could further provide us detail on the prediction of various domain-specific parameters in various perspectives.

The general classification of desalination technologies is physical and chemical methods [45] as presented in Fig. 4.

The design and operation of the seawater desalination plant are complex due to various social and environmental factors based on the classification and AI techniques that could serve better for decision making, parameter prediction, parameter optimization, and control [44]. From the analysis provided above ANN and GA has a higher chance of optimizing the desalination process and could be

Table 3
AI for desalination

S. No.	Description	Technique	Efficiency	Reference
1.	Flux, conductivity control for the reverse osmosis (RO) desalination	Model-free sliding mode and fuzzy controllers	–	[9]
2.	RO plant efficacy is assessed based on total dissolved solids (TDS) prediction	Multilayer perceptron hybrid with particle swarm optimization	52%	[10]
3.	Active power filters are allocated	Genetic algorithm (GA), and particle swarm optimization (PSO)	25% power saving	[11]
4.	RO design	Whale optimization algorithm	–	[12]
5.	Ranking the sustainability	Fuzzy logic – Mamdani	61%–70% Ranking	[13]
6.	Desalination flow control by tuning proportional integral derivative online	Fuzzy reinforcement learning	Improved	[14]
7.	Optimization of membrane	AI	Minimizing waste	[15]
8.	RO monitoring for a longer period	Artificial neural network (ANN) with a tree model	Performance analysis	[16]
9.	Membrane physical state analysis	Neural network	Consistent	[17]
10.	Performance estimate	ANN	–	[18]
11.	Performance estimate of heat pump	ANN	Prediction is better	[19]
12.	Multi-stage flashing optimization	ANN	–	[20]
13.	Water permeability assessment	Neural network	–	[21]
14.	Fault detection	Machine learning	95%	[22]

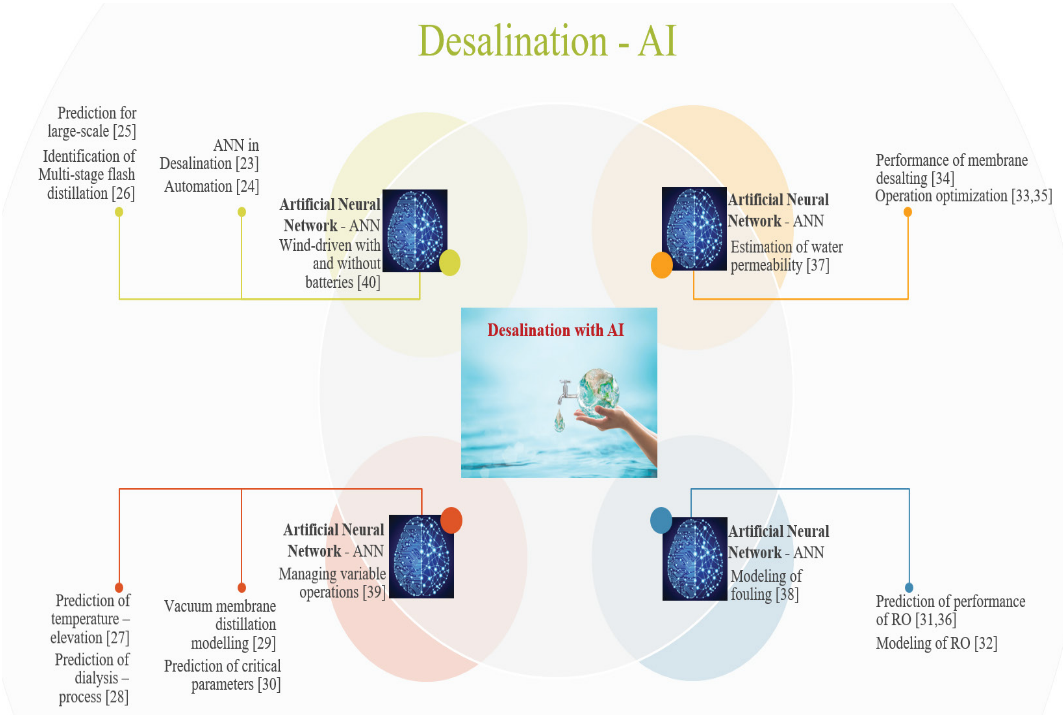

Fig. 3. Operation over desalination by AI technique.

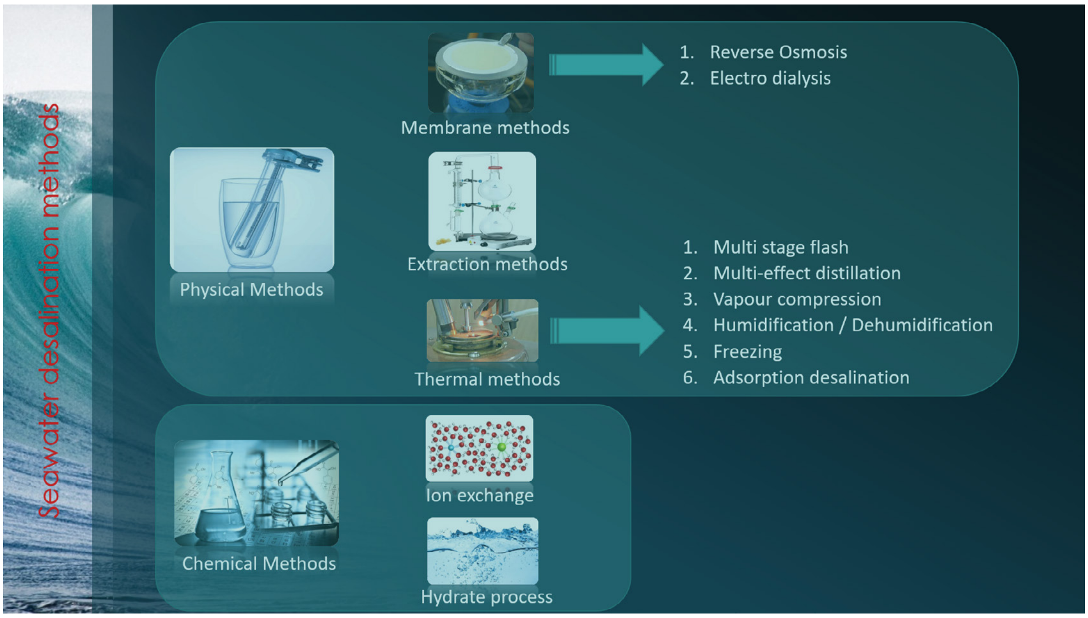

Fig. 4. Schematic of desalination methods [44].

interpreted in the other way as the techniques suitable for the renewable energy-driven desalination system.

3. Future of desalination – a landscape analysis

The volume of work in any field of research is measured by the number of publications that are available as reviews and implementation results. Today, Patents are considered to be one of the significant factors to analyze the research work carried out and products being developed. The patent landscape analysis is one of the ways to sight the growth of any process under study. The patent landscape analysis provides an update of day-to-day activities in the field when compared to articles, and journals, in which case the updations are not so fast and also hard to consolidate the yearly evolution and segregation and not flexible as with patent

Table 4
Landscape analysis artificial intelligence-based desalination [41]

S. No.	Country	Major applicants	Year-wise count
1.	USA – 85	Strong Force IoT Portfolio 2016 LLC – 55	2014 – 3
2.	PCT – 34	Al Mazeedi Wael Faisal – 11	2015 – 5
3.	EPO – 4	Sampson Glenn A – 5	2016 – 4
4.	Australia – 3	Friesth Kevin Lee – 4	2017 – 6
5.	Canada – 3	GDO Inc. – 4	2018 – 31
6.	China – 2	Breakthrough Tech. LLC. – 3	2019 – 32
7.	Finland – 1	Kevin Lee Friesth – 3	2020 – 20
8.		Lone Gull Holdings, Ltd. – 3	2021 – 9
9.		BTU Research LLC – 2	

EPO – European Patent Office – EPO; PCT – Patent Cooperation Treaty

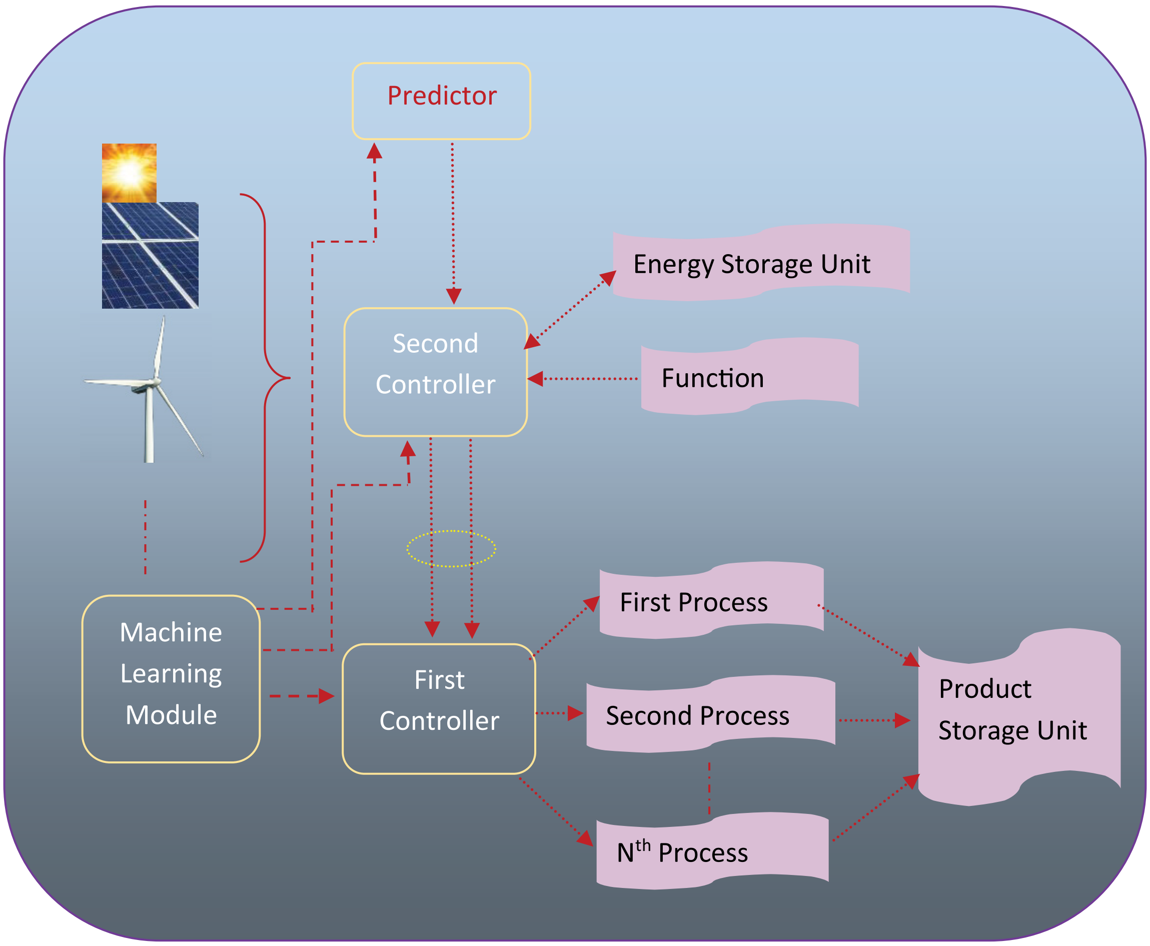

Fig. 5. AI-controlled desalination [42].

database. The prediction is done based on the current trends in filing the patents that focus on the process of desalination during the year 2021. The graph below provides an insight into the trend of desalination that uses AI. The landscape depicts that the USA is quite dominant in AI technology, in particular in the field of desalination. No other country is found to have such a considerable count. "Strong force IoT portfolio 2016 LLC" is the applicant with a major contribution of around 55 patents related to AI-based desalination, again the count is far from the competitors. It further reveals that the experts in the domain know the implication of this technology in a varied domain, so considerable research is in progress. The last decade filing reveals that initially during 2014 it was sluggish and gradually there is

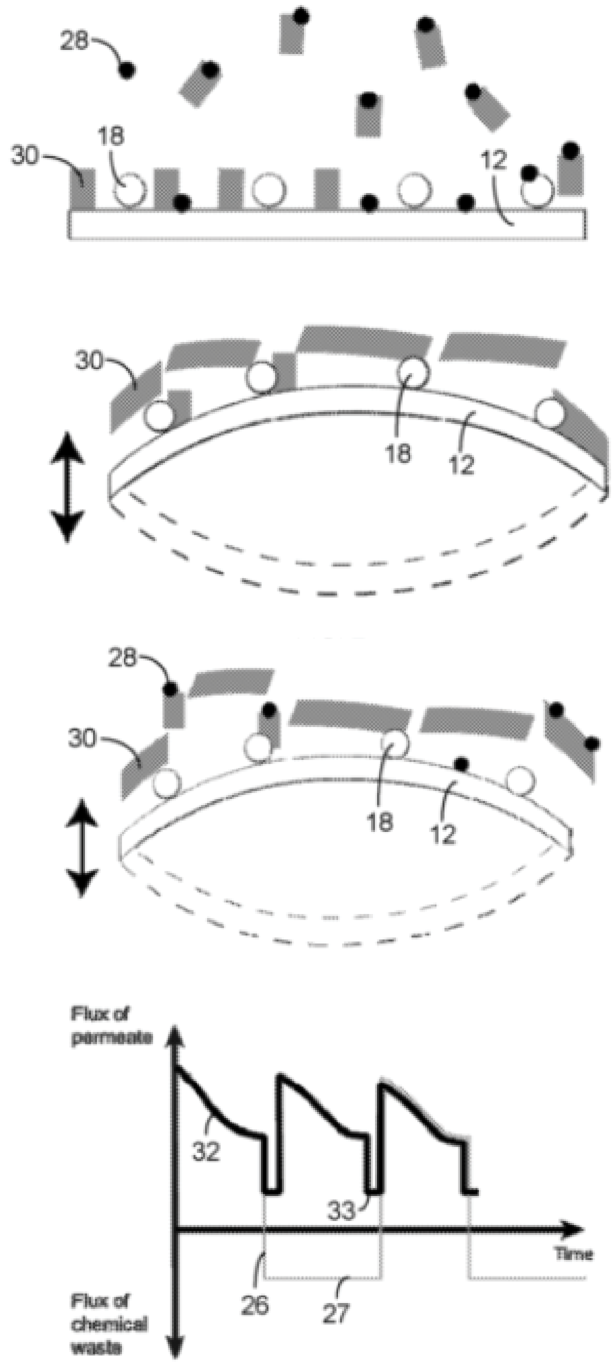

Fig. 6. AI-based desalination [43].

a raise, but there was a sudden peak during the year 2018 and still, the count is progressive. It reveals the significance of AI technology in the process of desalination. The landscape analysis gives a picture of the accelerating growth when the latest technologies are being used for optimization. The graphs are plotted as a result of the patent landscape analysis based on three main parameters namely year of publication, applicants, and publishing country.

The total count is 132 as per the record for the keyword EN_ALL: ("artificial intelligence" "desalination") with "single-family member", which means the same patent filed in different countries is omitted and considered as one patent.

The patent analysis on desalination using AI reveals further that the technologies developed by the Massachusetts Institute of Technology (MIT), USA have potential scope soon. A deep discussion on the technologies is provided herewith. It is tabulated in Table 4.

3.1. Time-variant multi-stage control system

A control system that has power and energy controlled at one or more levels. The initial controller is fixed at a level that optimally separates power in-between as a minimum of two processes to increase instantaneous output with the limited amount of power currently available. The electricity is optimally separated between the ion exchange membranes and the pumps, increasing the instantaneous production of desalinated water for a certain amount of electricity using electrodialysis reversal (EDR) desalination. An optional controller at another level is fixed that separates the power that is time-variant between the processes at the first level controller and the storage unit based on energy, future power availability, and performance forecast. In the case of EDR, the electricity generated by the photovoltaic (PV) line is divided between the EDR and the desalination process by the battery, which is the future PV [42]. It is revealed in the Fig. 5.

3.2. Deformation-enhanced cleaning of fouled membranes

Controlled decomposition is some to perform enhanced cleaning of a contaminated membrane, where-in a feed mixture consisting of a solvent and dissolved components flows to the retention side of a membrane block. The solvent rushes through the membrane from the retention side to the side of an infiltration or membrane block. When a stain forms on both sides of the membrane, a driving force is generated throughout the membrane, in which the membrane responds by rotating back and forth or pulling to the side, sideways. The stain-membrane interface caused by membrane deformation is expelled from the membrane via mechanical fatigue and is in contact with a spacer in contact with the membrane [43]. It is revealed in the Fig. 6.

4. Summary and conclusion

The future and growth of the desalination process are assessed with the aid of AI techniques. AI provides the greatest support in assessing the performance of the desalination process as well as could be used to optimize the process. The desalination using AI techniques has various advantages including reduction of wastage, increase in efficiency, better prediction, and so on. The AI-based desalination is predicted to provide a measurable method providing accurate and efficient techniques that could best suit the desalination process by considering the various evaluation parameters. The proposed review is aimed at providing the statistical validations that could guide the researchers to focus on the optimization of the desalination techniques to prevent the issue of water scarcity instead of a blind fixation on suitable techniques. The patent landscape analysis makes focuses on the research progress and hence depicts the growth of technology not only for the desalination process but also in evaluating the process. The combination of classical modeling methods and AI tools or techniques could generate a higher potential to enable optimal operations, in complex operating environments particularly. The scope of a hybrid intelligent system is growing popular in recent years, as more real-world complex problems could be handled easier and better.

References

[1] https://www.waterworld.com/international/wastewater/article/16201682/analysis-global-water-stress-by-2040, Accessed on 20th June 2021.

[2] R. Al Hashemi, S. Zarreen, A. Al Raisi, F.A. Al Marzooqi, S.W. Hasan, A review of desalination trends in Gulf Cooperation Council Countries, Int. J. Sci. Res., 2 (2014) 72–96.

[3] https://www.iea.org/commentaries/desalinated-water-affects-the-energy-equation-in-the-middle-east, Accessed on 20th June 2021.

[4] M.A. Darwish, H.K. Abdulrahim, A.S. Hassan, A.A. Mabrouk, PV and CSP solar technologies & desalination: an economic analysis, Desal. Water Treat., 57 (2016) 16679–16702.

[5] M. Sadi, H. Fakharian, H. Ganji, M. Kakavand, Evolving artificial intelligence techniques to model the hydrate-based desalination process of produced water, J. Water Reuse Desal., 9 (2019) 372–384.

[6] S. AlZu'bi, M. Alsmirat, M. Al-Ayyoub, Y. Jararweh, Artificial Intelligence Enabling Water Desalination Sustainability Optimization, 2019 7th International Renewable and Sustainable Energy Conference (IRSEC), IEEE, Agadir, Morocco, 2019, pp. 1–4.

[7] N. Parveen, S. Zaidi, M. Danish, Artificial intelligence (AI)-based reverse osmosis water desalination models, IWRA (India) J., 8 (2019) 44–50.

[8] Y. Wang, Z. Cao, A. Barati Farimani, Ozark nanopore: highly efficient and selective graphene nanopore designed by artificial intelligence for water desalination, Bull. Am. Phys. Soc., (2020), 2020APS.DFDJ16004W.

[9] S. Vrkalovic, E.-C. Lunca, I.-D. Borlea, Model-free sliding mode and fuzzy controllers for reverse osmosis desalination plants, Int. J. Artif. Intell., 16 (2018) 208–222.

[10] M. Ehteram, S.Q. Salih, Z.M. Yaseen, Efficiency evaluation of reverse osmosis desalination plant using hybridized multilayer perceptron with particle swarm optimization, Environ. Sci. Pollut. Res., 27 (2020) 15278–15291.

[11] H.M. El-Arwash, A.M. Azmy, E.M. Rashad, A GA-Based Initialization of PSO for Optimal APFS Allocation in Water Desalination Plant, 2017 Nineteenth International Middle East Power Systems Conference (MEPCON), IEEE, Cairo, Egypt, 2017, pp. 1378–1384.

[12] N.S. Rathore, V.P. Singh, Whale optimization algorithm-based controller design for reverse osmosis desalination plants, Int. J. Intell. Eng., 7 (2019) 77–88.

[13] R. Rustum, A.M.J. Kurichiyanil, S. Forrest, C. Sommariva, A.J. Adeloye, M. Zounemat-Kermani, M. Scholz, Sustainability ranking of desalination plants using mamdani fuzzy logic inference systems, Sustainability, 12 (2020) 631, doi: 10.3390/su12020631.

[14] P. Kofinas, A.I. Dounis, Online tuning of a PID controller with a fuzzy reinforcement learning MAS for flow rate control of a desalination unit, Electronics, 8 (2019) 231, doi: 10.3390/electronics8020231.

[15] M.T. Gaudio, G. Coppola, L. Zangari, S. Curcio, S. Greco, S. Chakraborty, Artificial intelligence-based optimization of industrial membrane processes, Earth Syst. Environ., 5 (2021) 385–398.

[16] Y. Choi, Y. Lee, K. Shin, Y. Park, S. Lee, Analysis of long-term performance of full-scale reverse osmosis desalination plant using artificial neural network and tree model, Environ. Eng. Res., 25 (2020) 763–770.

[17] A.V. Dudchenko, M.S. Mauter, Neural networks for estimating physical parameters in membrane distillation, J. Membr. Sci., 610 (2020) 118285, doi: 10.1016/j.memsci.2020.118285.

[18] P. Gao, L. Zhang, K. Cheng, H. Zhang, A new approach to performance analysis of a seawater desalination system by an artificial neural network, Desalination, 205 (2007) 147–155.

[19] M. Faegh, P. Behnam, M.B. Shafii, M. Khiadani, Development of artificial neural networks for performance prediction of a heat pump assisted humidification-dehumidification desalination system, Desalination, 508 (2021) 115052.

[20] K.A. Al-Shayji, S. Al-Wadyei, A. Elkamel, Modelling and optimization of a multistage flash desalination process, Eng. Optim., 37 (2005) 591–607.

[21] M. Barello, D. Manca, R. Patel, I.M. Mujtaba, Neural network based correlation for estimating water permeability constant in RO desalination process under fouling, Desalination, 345 (2014) 101–111.

[22] M. Derbali, S.M. Buhari, G. Tsaramirsis, M. Stojmenovic, H. Jerbi, M.N. Abdelkrim, M.H. Al-Beirutty, Water desalination fault detection using machine learning approaches: a comparative study, IEEE Access, 5 (2017) 23266–23275.

[23] M.E. El-Hawary, Artificial neural networks and possible applications to desalination, Desalination, 92 (1993) 125–147.

[24] G.P. Rao, D.M.K. Al-Gobaisi, A. Hassan, A. Kurdali, R. Borsani, M. Aziz, Towards improved automation for desalination processes, Part II: intelligent control, Desalination, 8 (1994) 507–528.

[25] K.A. Al-Shayji, Y.A. Liu, Predictive modeling of large-scale commercial water desalination plants: data-based neural network and model-based process simulation, Ind. Eng. Chem. Res., 41 (2002) 6460–6474.

[26] R. Selvaraj, P.B. Deshpande, S.S. Tambe, B.D. Kulkami, Neural networks for the identification of MSF desalination plants, Desalination, 101 (1995) 185–193.

[27] A. Aminian, Prediction of temperature elevation for seawater in multi-stage flash desalination plants using radial basis function neural networks, Chem. Eng. J., 162 (2010) 552–556.

[28] H.R. Godini, M. Ghadrdan, M.R. Omidkhah, S.S. Madaeni, Part II: prediction of the dialysis process performance using artificial neural network (ANN), Desalination, 265 (2011) 11–21.

[29] W. Cao, Q. Liu, Y. Wang, I.M. Mujtaba, Modeling and simulation of VMD desalination process by ANN, Comput. Chem. Eng., 84 (2016) 96–103.

[30] M.M. Jafar, A. Zilouchian, Prediction of critical desalination parameters using radial basis functions networks, J. Intell. Rob. Syst., 34 (2002) 219–230.

[31] Z.V.P. Murthy, M.M. Vora, Prediction of reverse osmosis performance using artificial neural network, Indian J. Chem. Technol., 11 (2004) 108–115.

[32] A. Abbas, N. Al-Bastaki, Modeling of an RO water desalination unit using neural networks, Chem. Eng. J., 114 (2005) 139–143.

[33] Y.G. Lee, Y.S. Lee, J.J. Jeon, S. Lee, D.R. Yang, I.S. Kim, J.H. Kim, Artificial neural network model for optimizing operation of a seawater reverse osmosis desalination plant, Desalination, 247 (2009) 180–189.

[34] D. Libotean, J. Giralt, F. Giralt, R. Rallo, T. Wolfe, Y. Cohen, Neural network approach for modeling the performance of reverse osmosis membrane desalting, J. Membr. Sci., 326 (2009) 408–419.

[35] S.S. Madaeni, M. Shiri, A.R. Kurdian, Modeling, optimization, and control of reverse osmosis water treatment in Kazeroon power plant using neural network, Chem. Eng. Commun., 202 (2015) 6–14.

[36] A.M. Aish, H.A. Zaqoot, S.M. Abdeljawad, Artificial neural network approach for predicting reverse osmosis desalination plants performance in the Gaza Strip, Desalination, 367 (2015) 240–247.

[37] M. Barello, D. Manca, R. Patel, I.M. Mujtaba, Neural network based correlation for estimating water permeability constant in RO desalination process under fouling, Desalination, 345 (2014) 101–111.

[38] E.A. Roehl, D.A. Ladner, R.C. Daamen, J.B. Cook, J. Safarik, D.W. Phipps, P. Xie, Modeling fouling in a large RO system with artificial neural networks, J. Membr. Sci., 552 (2018) 95–106.

[39] P. Cabrera, J.A. Carta, J. González, G. Melián, Artificial neural networks applied to manage the variable operation of a simple seawater reverse osmosis plant, Desalination, 416 (2017) 140–156.
[40] P. Cabrera, J.A. Carta, J. González, G. Melián, Wind-driven SWRO desalination prototype with and without batteries: a performance simulation using machine learning models, Desalination, 435 (2018) 77–96.
[41] https://patentscope.wipo.int/search/en/result.jsf?_vid=P21-KQAPUT-18101, Accessed on 24th June 2021.
[42] https://patentscope.wipo.int/search/en/detail.jsf?docId=WO2021081132&_cid=P20-KR5Y30-38784-1, Accessed on 24th June 2021.
[43] https://patentscope.wipo.int/search/en/detail.jsf?docId=WO2021072345&tab=PCTBIBLIO&_cid=P20-KR5YT1-47461-1, Accessed on 24th June 2021.
[44] Q. He, H. Zheng, X. Ma, L. Wang, H. Kong, Z. Zhu, Artificial intelligence application in a renewable energy-driven desalination system: a critical review, Energy AI, 7 (2022) 100–123.
[45] A. Subramani, J.G. Jacangelo, Emerging desalination technologies for water treatment: a critical review, Water Res., 75 (2015) 164–187.