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Prediction of distillate output in photocatalytic solar still using artificial intelligence (AI)

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Abstract. Solar desalination is widely employed technology to separate potable water from saline water. In this study a solar still with one slope was employed to desalinate the saline water. The bottom plate of the solar still was coated with titanium dioxide to improve its performance. The distillate output was collected at three depths of water level in the still for different time intervals. Artificial Intelligence-Levenberg Marquardt (AI-LM) method was employed to predict the distillate output. The predicted values for the response were found to be in good agreement (R^2 = 0.997) with the experimental data.

Introduction

Water is one of the most abundant resources on Earth since it is necessary for human activity and all ecosystems. As the population grows, so does the demand for drinkable water. Large amounts of fresh water are required in every corner of the world for agricultural, industrial, and household purposes [1]. Oceans are a large supply of water, but they are not suitable for human consumption due to their salt [2]. Several writers reported on research in the field of solar desalination, which is the most prominent and cost-effective method, requiring simple technology and maintenance [3]. A single slope solar still is one of the best solar desalination devices, and numerous efforts are being made to improve its productivity [4].

The light absorber's evaporation efficiency remained practically unchanged after thirty cycles of evaporation and condensation. The photothermal layer's excellent light-harvesting properties, its ability to withstand heat, and the substrate's abundance of open channels allow for the system's exceptional photothermal performance for long-term solar desalination [5]. As the contact period extended up to six hours, the salt content progressively reduced by more than 25%. There is no discernible shift in the water's pH has occurred. Salinity in seawater can be efficiently decreased by the hybrid titanium di oxide (TiO_2) [6]. The combined photocatalytic and photothermal system has a high solar energy utilization efficiency and may be used to clean wastewater and produce potable water in one unit [7]. The cost of generating water using solar-based desalination techniques remains greater than that of typical fossil-fuel-based desalination facilities, owing mostly to the high cost of solar collectors. This is one of the primary issues limiting commercialization rates. Residue removal may be expensive in terms of water use and have unfavorable consequences on the environment [8].

Due to the synergistic impact of Polydopamine (PDA) / TiO_2 nanoparticles, the Janus evaporator can breakdown over 95% of organic dyes (such as Congo red and trypan blue) and efficiently desalinate and purify other unusual water sources. Potential uses for this Janus structured hydrogel evaporator include desalination and wastewater treatment [9]. The most intriguing aspect is that the solar-driven photothermal effect may potentially be used by a number of other water purification technologies [10]. With the help of an efficient monolithic material platform and a straightforward, reusable, portable, and reasonably priced solar thermal water purification system, water filtration for a range of environmental conditions is revolutionized [11].

Under the sun (i.e., 1 kW m^{-2}), the TiO_2-CuO-Cufoam evaporator concurrently exhibits high solar evaporation efficiency of 86.6% and efficiency of 80.0% for the elimination of volatile organic compounds (VOCs) [12]. The photocatalytic hydrogen generation process is a straightforward and economical technique used to produce solar hydrogen by imitating artificial photosynthesis [13]. The traditional method of desalination using passive solar stills relies solely on sun radiation as a source of thermal energy [14]. Seawater desalination by membrane distillation is believed to be attainable by the direct joule heating of the water-hydrophobic membrane interface utilizing a porous thin-film carbon nanotube [15].

Artificial Intelligence-Levenberg Marquardt (AI-LM) in Solar Still Systems

An artificial neural network (ANN) was created to investigate the role of the photocatalyst in the desalination process and supply the quantity of distillate needed for solar photocatalytic modelling. Water is produced via desalination for a variety of uses, including home usage, industrial processing, and water delivery [16]. Desalination methods most commonly used include membrane processes Reverse Osmosis (RO) or thermal desalination [17]. Three data sets training, validation, and test were created using the Fujairah sea water reverse osmosis (SWRO) plant's one-year operating data (n = 200) in order to create the ANN model. Good agreement was produced between the simulated and observed data in the test data set by the trained ANN model (TDS: R^2 = 0.96; flow rate: R^2 = 0.75) [18].

Reverse/Back propagation radial basis function (RBF) neural networks and a multilayer perception (MLPs) trained with the Rprop approach are used to forecast pH values. When the created models were compared to the linear regression methodology, it was found that the MLP and RBF neural network forecasts outperformed those of the conventional methods [19]. An effective method for handling complex and stochastic systems that only accept time series data as input variables and don't fully comprehend physical or hydrogeological components is the artificial neural network (ANN) [20]. With the Nash-Sutcliffe efficiency coefficient of 0.964, the correlation coefficient of 0.983, and the root mean square error of 1.052 km^2, the integrated model showed that this approach effectively reproduced static integrated analysis (SIA) variations [21]. Moreover, the ANN algorithm's performance was assessed in October 1999, during a super storm over the Bay of Bengal [22].

Al-Ghamdi et al., assess the effectiveness of ANNs for short-term water demand forecasting in Jeddah, Saudi Arabia, using a variety of normalization techniques (min-max, z-score, decimal, median, and Median Absolute Deviation (MAD) [23]. The ANN approach has been used to the calibration of an industrial prototype microwave six-port equipment, yielding great accuracy across a broad dynamic range [24] and [25]. Freshwater shortage is a major global concern due to the dramatic increase in demand for freshwater for drinking and personal use that has occurred as a result of population growth. The usefulness of machine learning in forecasting the performance of solar stills has been updated to the point where it is now a central component of numerous studies. Regardless of the size of the dataset, multiple regression models can display a moderate level of prediction accuracy. As opposed to multiple regression models, ANN (Artificial Neural Network) models have an accuracy that is greater and are influenced by dataset sizes ranging from 100 to 400. The models varied in terms of prediction accuracy. Support vector machines, artificial neural networks (ANNs), back-propagation ANNs, and random forests based on Bayesian optimization demonstrated strong prediction ability for hemispheric, inched, tubular, double-slope, and single-slope SSs, respectively. Several models were tested to anticipate thermal efficiency; the highest accurate prediction was produced at six input neurons using an ANN in combination with the Imperialist Competition Algorithm, with an RMSE (root mean square error) of 1.3673 [26].

To anticipate the solar still performance characteristics, a back propagation artificial neural network model was created. For the purpose of predicting solar still performance, the applicability and efficacy of artificial neural networks (ANNs) considering a number of operational and meteorological factors have been assessed. The five input variables pertaining to weather conditions were air temperature (T_o), relative humidity (RH), wind speed (U), solar radiation (Rs), and ultraviolet index (UVI); the four variables pertaining to system operational conditions were brine temperature, feed water temperature, total dissolved solids of brine (TDSB), and brine temperature. The last variable was the number of days, or Julian day (J). Testing and validation processes utilizing statistical criteria indicate that the created artificial neural network (ANN) model may provide extremely high efficiency results, confirming its usability and usefulness in solar desalination prediction. These results bolster the hypothesis that the built artificial neural network (ANN) model correctly anticipated the performance parameters of the solar still.

The primary advantage of the artificial neural network (ANN) model for solar desalination performance prediction is its ease of use, since it can be implemented with ease using any spreadsheet or computer language. The ANN model produced the contribution ratio, which shows how each input variable affects the outputs. In the ANN model for MD and gth prediction, TF is the input parameter with the highest contribution ratio. However, when it comes to objective response rate (ORR) prediction, ultra violet index (UVI) has the biggest contribution ratio. The study also demonstrated the usefulness and effectiveness of artificial neural networks (ANNs), which can forecast solar still performance without the need for additional trials and may result in time, effort, and resource savings [27].

Artificial neural networks, or ANNs, are sophisticated mathematical representations of the nervous system of humans. Over the last three decades, there has been a noticeable surge in the use of artificial neural networks (ANNs) for problem classification, pattern recognition, regression, and forecasting. The input layer, which is the initial layer in a multilayer perception (MLP) architecture, provides input variables to the network. The layers that are located between the input and output levels are known as hidden layers, and the output layer is the last layer. One of the most popular FFNNs is the multilayer perceptron (MLP) neural network. In multilevel perception (MLP), the unidirectional connections between neurons are represented by weights, which are the actual numbers present in the interval [28].

A thorough analysis of recent advancements using Nano/micro materials in solar stills is given. The majority of current efforts have focused on enhancing solar evaporation, which is only one of the fundamental processes in a solar still. To increase the system's productivity and efficiency, a variety of materials were used, including paper-based film, synthetic aerogel, and natural biomaterials. When combined with optimum thermal design and heat localization at the air-water interface, suitable materials can potentially attain an efficiency of over 90% when exposed to 1 kw/m^2 of solar energy. However, even with the application of these materials, productivity is still low. This demonstrates how different solar evaporation systems are from sun stills [30].

Case Study

The still was filled with saline water and exposed to natural sunlight. Three different levels of water were considered and at each level the distillate output was measured for various time intervals. The bottom plate of the still was coated with photocatalyst (Titanium dioxide) to enhance the performance of the still. Figure 1 displays the schematic diagram for the still.

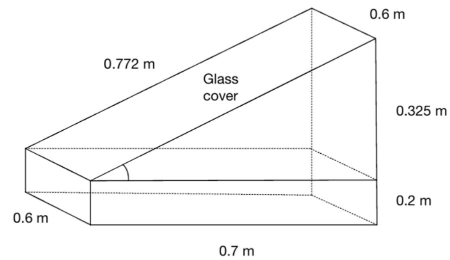

Fig 1. Schematic Diagram of Solar Still

The experimental data was utilized to test, train and predict the distillate output using ANN-LM algorithm. The Levenberg-Marquardt algorithm (LM) and damped least squares (DLS) approach were utilized in MATLAB R2023 by Math Works, Inc. to optimize the input variables [31]. A MATLAB tool called the Artificial Neural Network is used to computationally model data variables in order to investigate the links between input and output in systems or processes [32]. The size of the network is similar to the number of neurons in the brains of living beings that enable intelligent behavior. It consists of input nodes for the input independent variables of the experimental data and output nodes for the factors or dependent variables of the response [33]. S neurons, multilayer neural networks, and a multi-layer network with R input components were all used in the current optimization technique. Three subsets of the data were used, comprising of 70%, 15%, and 15% of the total [34]. Two subsets are utilized for testing and validation, and the first subset is used for training. The distillation target values and model output are displayed in Figure 2. The comparison of the experimental and expected values is displayed in Table 1.

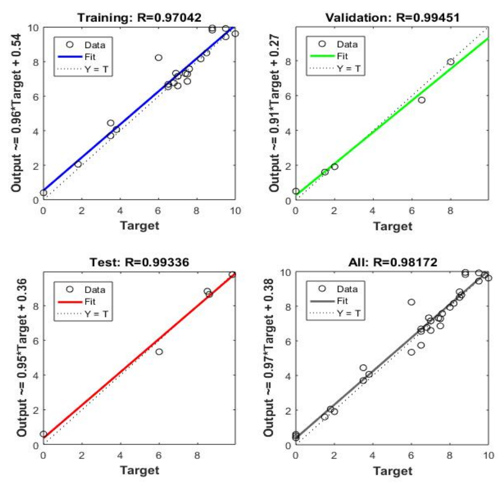

Fig 2. ANN network model output values and the target values of distillate still

Table 1. Experimental and ANN-LM Predicted Data

Depth, m	Time, hours	Solar Radiation W/m^2	Amount of Distillate m^3	Prediction
0.0333	8	500	0	0.00000402
0.0333	9	727	0.000015	0.00001605
0.0333	10	932	0.000035	0.00003705
0.0333	11	1045	0.00006	0.00005340
0.0333	12	1136	0.000065	0.00006545
0.0333	13	1114	0.00008	0.00007937

0.0333	14	1023	0.000095	0.00009445
0.0333	15	886	0.000085	0.00008508
0.0333	16	682	0.000075	0.00006860
0.0333	17	409	0.00007	0.00007149
0.0333	18	200	0.00006	0.00008233
0.025	8	500	0	0.00000509
0.025	9	727	0.00002	0.00001913
0.025	10	932	0.000038	0.00004068
0.025	11	1045	0.000065	0.00005742
0.025	12	1136	0.000075	0.00007279
0.025	13	1114	0.000085	0.00008831
0.025	14	1023	0.000098	0.00009792
0.025	15	886	0.000088	0.00009828
0.025	16	682	0.000076	0.00007577
0.025	17	409	0.00007	0.00006599
0.025	18	200	0.000065	0.00006684
0.0133	8	500	0	0.00000598
0.0133	9	727	0.000018	0.00002056
0.0133	10	932	0.000035	0.00004447
0.0133	11	1045	0.000068	0.00006771
0.0133	12	1136	0.000086	0.00008650
0.0133	13	1114	0.0001	0.00009622
0.0133	14	1023	0.000095	0.00009924
0.0133	15	886	0.000088	0.00009948
0.0133	16	682	0.000082	0.00008161
0.0133	17	409	0.000074	0.00007310
0.0133	18	200	0.000069	0.00007328

Results and Discussion

The use of Artificial Intelligence (AI) Levenberg Marquardt method in predicting the distillate output for a photocatalytic solar still has yielded promising results. The AI models, including machine learning algorithms and neural networks, demonstrated high accuracy in forecasting distillate output based on various input parameters such as time and solar radiation. These models were able to effectively capture the complex relationships between these factors and distillate output, leading to precise predictions. The application of AI in this context offers several advantages, including improved operational efficiency, better planning of distillation processes, and enhanced performance of photocatalytic solar stills.

Conclusion

Solar photocatalytic still was employed to desalinate the saline water. The output distillate was collected at three depths of water levels for various time intervals. The experimental data was utilized to train, test and predict the distillate output using artificial neural network-Levenberg Marquardt ANN-LM algorithm. The expected values and the experimental values were found to be in good agreement for the response with an average of $R^2 = 0.997$.

References

[1] N. Mohammed, P. Palaniandy, F. Shaik, and H. Mewada, "Statistical Modelling of Solar Photocatalytic Biodegradability of Seawater Using Combined Photocatalysts," *J. Inst. Eng. India Ser. E*, Sep. 2023. https://doi.org/10.1007/s40034-023-00274-8

[2] N. Mohammed, P. Palaniandy, F. Shaik, H. Mewada, and D. Balakrishnan, "Comparative studies of RSM Box-Behnken and ANN-Anfis fuzzy statistical analysis for seawater biodegradability using TiO2 photocatalyst," *Chemosphere*, vol. 314, p. 137665, Feb. 2023. https://doi.org/10.1016/j.chemosphere.2022.137665

[3] F. Shaik, S. S. R. Al Siyabi, N. Mohammed, and M. Eltayeb, "Assessment of ground and surface water quality and its contamination," *International Journal of Environmental Analytical Chemistry*, vol. 103, no. 6, pp. 1449–1467, May 2023. https://doi.org/10.1080/03067319.2021.1873975

[4] N. Mohammed, P. Palaniandy, F. Shaik, and H. Mewada, "EXPERIMENTAL AND COMPUTATIONAL ANALYSIS FOR OPTIMIZATION OF SEAWATER BIODEGRADABILITY USING PHOTO CATALYSIS," *IIUMEJ*, vol. 24, no. 2, pp. 11–33, Jul. 2023. https://doi.org/10.31436/iiumej.v24i2.2650

[5] M. Shafaee, E. K. Goharshadi, M. M. Ghafurian, M. Mohammadi, and H. Behnejad, "A highly efficient and sustainable photoabsorber in solar-driven seawater desalination and wastewater purification," *RSC Adv.*, vol. 13, no. 26, pp. 17935–17946, 2023. https://doi.org/10.1039/D3RA01938A

[6] R. Isha and N. H. Abd Majid, "A Potential Hybrid TiO_2 in Photocatalytic Seawater Desalination," *AMR*, vol. 1113, pp. 3–8, Jul. 2015. https://doi.org/10.4028/www.scientific.net/AMR.1113.3

[7] L. Shi *et al.*, "An Integrated Photocatalytic and Photothermal Process for Solar-Driven Efficient Purification of Complex Contaminated Water," *Energy Tech*, vol. 8, no. 9, p. 2000456, Sep. 2020. https://doi.org/10.1002/ente.202000456

[8] Y. Zhang, M. Sivakumar, S. Yang, K. Enever, and M. Ramezanianpour, "Application of solar energy in water treatment processes: A review," *Desalination*, vol. 428, pp. 116–145, Feb. 2018. https://doi.org/10.1016/j.desal.2017.11.020

[9] J. Wen *et al.*, "Architecting Janus hydrogel evaporator with polydopamine-TiO2 photocatalyst for high-efficient solar desalination and purification," *Separation and Purification Technology*, vol. 304, p. 122403, Jan. 2023. https://doi.org/10.1016/j.seppur.2022.122403

[10] Y. Lu, H. Zhang, D. Fan, Z. Chen, and X. Yang, "Coupling solar-driven photothermal effect into photocatalysis for sustainable water treatment," *Journal of Hazardous Materials*, vol. 423, p. 127128, Feb. 2022. https://doi.org/10.1016/j.jhazmat.2021.127128

[11] Y. Yang *et al.*, "Graphene-Based Standalone Solar Energy Converter for Water Desalination and Purification," *ACS Nano*, vol. 12, no. 1, pp. 829–835, Jan. 2018. https://doi.org/10.1021/acsnano.7b08196

[12] Y. Tian *et al.*, "High-performance water purification and desalination by solar-driven interfacial evaporation and photocatalytic VOC decomposition enabled by hierarchical TiO_2-CuO nanoarchitecture," *Intl J of Energy Research*, vol. 46, no. 2, pp. 1313–1326, Feb. 2022. https://doi.org/10.1002/er.7249

[13] M. S. Yesupatham *et al.*, "Photocatalytic seawater splitting for hydrogen fuel production: impact of seawater components and accelerating reagents on the overall performance," *Sustainable Energy Fuels*, vol. 7, no. 19, pp. 4727–4757, 2023. https://doi.org/10.1039/D3SE00810J

[14] R. Djellabi *et al.*, "Recent advances and challenges of emerging solar-driven steam and the contribution of photocatalytic effect," *Chemical Engineering Journal*, vol. 431, p. 134024, Mar. 2022. https://doi.org/10.1016/j.cej.2021.134024

[15] M. Fujiwara and M. Kikuchi, "Solar desalination of seawater using double-dye-modified PTFE membrane," *Water Research*, vol. 127, pp. 96–103, Dec. 2017. https://doi.org/10.1016/j.watres.2017.10.015

[16] N. Mohammed, A. Asiz, M. A. Khasawneh, H. Mewada, and T. Sultana, "Machine learning and RSM-CCD analysis of green concrete made from waste water plastic bottle caps: Towards performance and optimization," *Mechanics of Advanced Materials and Structures*, pp. 1–9, Aug. 2023. https://doi.org/10.1080/15376494.2023.2238220

[17] N. Mohammed, P. Palaniandy, and F. Shaik, "Pollutants removal from saline water by solar photocatalysis: a review of experimental and theoretical approaches," *International Journal of Environmental Analytical Chemistry*, vol. 103, no. 16, pp. 4155–4175, Dec. 2023. https://doi.org/10.1080/03067319.2021.1924160

[18] Y. G. Lee *et al.*, "Artificial neural network model for optimizing operation of a seawater reverse osmosis desalination plant," *Desalination*, vol. 247, no. 1–3, pp. 180–189, Oct. 2009. https://doi.org/10.1016/j.desal.2008.12.023

[19] H. Adel Zaqoot, A. Baloch, A. Khalique Ansari, and M. Ali Unar, "APPLICATION OF ARTIFICIAL NEURAL NETWORKS FOR PREDICTING pH IN SEAWATER ALONG GAZA BEACH," *Applied Artificial Intelligence*, vol. 24, no. 7, pp. 667–679, Aug. 2010. https://doi.org/10.1080/08839514.2010.499499

[20] S. Al Ajmi, M. Ali Syed, F. Shaik, M. Nayeemuddin, D. Balakrishnan, and V. R. Myneni, "Treatment of Industrial Saline Wastewater Using Eco-Friendly Adsorbents," *Journal of Chemistry*, vol. 2023, pp. 1–11, Apr. 2023. https://doi.org/10.1155/2023/7366941

[21] D. Li *et al.*, "Simulation of Seawater Intrusion Area Using Feedforward Neural Network in Longkou, China," *Water*, vol. 12, no. 8, p. 2107, Jul. 2020. https://doi.org/10.3390/w12082107

[22] B. Jena, D. Swain, and A. Tyagi, "Application of Artificial Neural Networks for Sea-Surface Wind-Speed Retrieval From IRS-P4 (MSMR) Brightness Temperature," *IEEE Geosci. Remote Sensing Lett.*, vol. 7, no. 3, pp. 567–571, Jul. 2010. https://doi.org/10.1109/LGRS.2010.2041632

[23] A.-B. Al-Ghamdi, S. Kamel, and M. Khayyat, "Evaluation of Artificial Neural Networks Performance Using Various Normalization Methods for Water Demand Forecasting," in *2021 National Computing Colleges Conference (NCCC)*, Taif, Saudi Arabia: IEEE, Mar. 2021, pp. 1–6. https://doi.org/10.1109/NCCC49330.2021.9428856

[24] Yi Liu, "Calibrating an industrial microwave six-port instrument using the artificial neural network technique," *IEEE Trans. Instrum. Meas.*, vol. 45, no. 2, pp. 651–656, Apr. 1996. https://doi.org/10.1109/19.492804

[25] N. N, A. Siva Kumaran K, A. A, A. V. S, and B. M. J, "Convolutional Neural Networks (CNN) based Marine Species Identification," in *2022 International Conference on Automation, Computing and Renewable Systems (ICACRS)*, Pudukkottai, India: IEEE, Dec. 2022, pp. 602–607. https://doi.org/10.1109/ICACRS55517.2022.10029109

[26] A. F. Mashaly, A. A. Alazba, A. M. Al-Awaadh, and M. A. Mattar, "Predictive model for assessing and optimizing solar still performance using artificial neural network under hyper arid environment," *Solar Energy*, vol. 118, pp. 41–58, Aug. 2015. https://doi.org/10.1016/j.solener.2015.05.013

[27] F. A. Essa, M. Abd Elaziz, and A. H. Elsheikh, "An enhanced productivity prediction model of active solar still using artificial neural network and Harris Hawks optimizer," *Applied Thermal Engineering*, vol. 170, p. 115020, Apr. 2020. https://doi.org/10.1016/j.applthermaleng.2020.115020

[28] A. O. Alsaiari, E. B. Moustafa, H. Alhumade, H. Abulkhair, and A. Elsheikh, "A coupled artificial neural network with artificial rabbits optimizer for predicting water productivity of different designs of solar stills," *Advances in Engineering Software*, vol. 175, p. 103315, Jan. 2023. https://doi.org/10.1016/j.advengsoft.2022.103315

[29] G. Peng *et al.*, "Micro/nanomaterials for improving solar still and solar evaporation -- A review." arXiv, Jun. 20, 2019. https://doi.org/10.48550/arXiv.1906.08461

[30] G. Peng *et al.*, "Potential and challenges of improving solar still by micro/nano-particles and porous materials - A review," *Journal of Cleaner Production*, vol. 311, p. 127432, Aug. 2021. https://doi.org/10.1016/j.jclepro.2021.127432

[31] N. Mohammed, P. Palaniandy, and F. Shaik, "Optimization of solar photocatalytic biodegradability of seawater using statistical modelling," *Journal of the Indian Chemical Society*, vol. 98, no. 12, p. 100240, Dec. 2021. https://doi.org/10.1016/j.jics.2021.100240

[32] N. Mohammed, P. Palaniandy, F. Shaik, B. Deepanraj, and H. Mewada, "Statistical analysis by using soft computing methods for seawater biodegradability using ZnO photocatalyst," *Environmental Research*, vol. 227, p. 115696, Jun. 2023. https://doi.org/10.1016/j.envres.2023.115696

[33] N. Mohammed, P. Palaniandy, and F. Shaik, "Solar photocatalytic biodegradability of saline water: Optimization using RSM and ANN," *AIP Conference Proceedings*, vol. 2463, no. 1, p. 020027, May 2022. https://doi.org/10.1063/5.0080297

[34] N. Mohammed, P. Palaniandy, and F. Shaik, "Advanced Oxidation Processes for the Treatment of Pollutants from Saline Water," *Removal of Pollutants from Saline Water: Treatment Technologies*, p. 95, 2021.