Kufa Journal of Engineering
Vol. 17, No. 3, July 2026, P.P. 438-452
Article history: Received 20 July 2025, last revised 7 October 2025, accepted 10 October 2025

REVERSE OSMOSIS PILOT PLANT EFFICIENCY ASSESSMENT USING ARTIFICIAL NEURAL NETWORK (ANN)

Roaa A Kadhim[1], Basim Hussein khadhair[2], and Mahdi Shanshal Jaafar[3]

[1] Civil Engineering, University of Baghdad, Baghdad, Iraq
Email:r.kadhim@coeng.uobaghdad.edu.iq.

[2] Civil Engineering, University of Baghdad, Baghdad, Iraq,
Email:dr.basimalobaidy@coeng.uobaghdad.edu.iq.

[3] Ministry of Science and Technology, Baghdad, Iraq.

https://doi.org/10.30572/2018/KJE/170325

ABSTRACT

Reverse osmosis (RO) is widely used for desalination and water treatment, but its efficiency depends on several operational factors. This study evaluates the performance of a commercial RO unit in treating concentrate water and applies an artificial neural network (ANN) model to predict permeate total dissolved solids (TDS) and RO removal efficiency. Data was collected over 60 days monitoring period, water quality parameters including pH, total dissolved solids (TDS), electrical conductivity (EC), and temperature were measured for feed, permeate, and concentrate water of the RO unit. The results indicated that the RO unit has shown good performance in removing salt from concentrate water and achieved an average removal efficiency of 95.7% with permeate water meeting Iraqi and WHO drinking water standards. A slight decrease in efficiency was observed with rising feedwater temperature, with the highest performance near (96.9%) recorded near 21.8 °C. The ANN model showed moderate predictive accuracy for permeate TDS (R^2 = 0.870) with TDS variability explaining the difference in model performance. In addition, the ANN model presented a strong predictive performance for removal efficiency (R^2 = 0.902). Compared with previous studies, this work demonstrates the feasibility of using ANN to model and predict RO performance with small experimental datasets. The results provide practical insights for employing RO units for the reuse of RO concentrate through a secondary RO unit, which could minimize water wastage and mitigate environmental impacts.

KEYWORDS

Reverse osmosis (RO), Artificial neural network (ANN), Concentrate water, permeate water, water quality prediction.

1. INTRODUCTION

Water is a necessary component of keeping life on Earth alive, and due to the development of human civilization increased the demand for freshwater, which is a naturally renewable resource that makes up a small percentage of the overall water resources on Earth. Furthermore, the proportion of potable resources is much lower, making freshwater resources very limited (Zioui et al., 2017). Almost 2.1 billion people lack access to clean drinking water worldwide, as reported by the World Health Organization (WHO), and by 2030, it is expected that half of humanity will be living in areas with water shortages (World Health Organization (WHO), 2022). To address this crisis, desalination technologies have emerged as essential solutions for securing reliable water supplies. Utilizing the available saltwater through desalination technology is one way to restore the depleting sources of freshwater, and it appears to be a potential source for future freshwater demands.

Among membrane desalination methods, reverse osmosis (RO) system has become the leading technology due to its efficiency in removing dissolved salts and contaminants (Nair and Kumar, 2013). RO process has been continuously increasing its market share and improving to become the controlling technology in the production of clean water (Mujtaba et al., 2017). RO operates by forcing saline water across a semi-permeable membrane, allowing water molecules to pass while retaining salts, organic matter, and other impurities by using osmotic pressure as a driving force (Alfonso et al., 2018). The RO membrane is a permeable sheet wrapped around a porous tube. The microporous membrane allows for the passage of very small molecules whose molecular size is smaller than the holes of the membrane (Lilane et al., 2020). The mass balance of flow around the reverse osmosis (RO) unit splits the feed saline water into two effluents: the permeate and concentrate, or brine water (Zarzo and Prats, 2018).

The performance of RO systems is commonly assessed by parameters such as salt rejection, recovery ratio, permeate flux, and removal efficiency (Wasfy, 2017). Wali et al. (2015) evaluated the functionality and performance of the RO system located in Howtat Bani Tamim city, Saudi Arabia. The results showed that the permeate water's TDS content was 28.79 mg/lit, compared to the input water's 2000 mg/lit, for a removal rate of 98.56%. The plant's total efficiency in terms of flow capacity was 87.68%. The removal efficiency of the entire unit is the proportion of a pollutant that is eliminated during the treatment procedure. Removal efficiency can provide a more accurate estimation of the specific pollutant reduction achieved by a plant and assesse a treatment plant's performance evaluation (Khan et al., 2014, Luo et al., 2014).

Despite their advantages, RO systems face operational challenges including membrane fouling, scaling, and sensitivity to feedwater quality. These issues can reduce efficiency and increase maintenance costs (Jamaly et al., 2014). There are different techniques that can be used to remove colloidal particles from the membrane, prevent membrane fouling and Zeta rod electrodes one of these methods. The results of applying this method experimentally showed that zeta rod enhanced the production of water, expanded the operating life of the membranes, and prevented the formation of particulates on the membrane (Abbas et al., 2021).

The direct environmental impacts of reverse osmosis concentrate (ROC) are biofilm formation, modifications to water circulation patterns and local habitat, and modifications to sediment transport patterns. ROC has more effects, including salinity, temperature, pH, residual compounds, and heavy metals (Kress, 2019). The disposal of brine solution is related to the increase in salt concentrations in water bodies that receive brine. Brine disposal is considered a great threat to our environment (Katal et al., 2020). Therefore, several technologies, including advanced treatment techniques and disposal methods, must be engaged to manage concentrated solutions produced by desalination processes (Kadhim et al., 2023a). Several techniques have been suggested for estimating the removal efficiency of commercial RO plants. Artificial neural network (ANN) neurons serve as a computational framework that simulates the way human brain neurons handle input signals and generate output signals. It serves as a tool to simulate complex connections between inputs (independent variables) and outputs (dependent variables) (IBM SPSS Neural Networks 20, 2011). Through the application of artificial neural network (ANN) models and experimental methods, the operational parameters of the marine desalination system were improved and compared. The results observed that the model of ANN has a decreased optimization error for the important RO system parameters, offering a new line of inquiry for studies on the effectiveness of reverse osmosis (Wang, 2016).

Most existing studies address RO performance in treating raw water sources, while limited attention has been given to reusing RO concentrate or rejected water through an additional RO stage. This gap leaves opportunities for reducing water loss and minimizing the environmental impacts of concentrate effluent. This study aims to evaluate and simulate the performance of a reverse osmosis (RO) pilot plant designed to treat and recover concentrate effluent generated from an existing RO unit in Baghdad, Iraq. In addition, an artificial neural network (ANN) model was applied to simulate and predict total dissolved solids (TDS) concentration in permeate water and RO removal efficiency based on the collected data.

2. MATERIAL AND METHOD

2.1. Case study description

A commercial RO plant was used for this study to evaluate the performance of the RO unit and the removal efficiency of concentrate water feed to the RO. RO units consist of pretreatment filters, booster pumps, RO membranes, post-treatment filters, and diaphragm storage tanks, as shown in Fig. 1. The pretreatment system removes different impurities that cause scaling and fouling problems in the membranes. The pretreatment stage consists of three stages: The polypropylene filter (Pp) is used to remove sand, silt, mud, and rust particles from water that might clog other filters in the purification system. Granular activated carbon (GAC) is used to remove chlorine, dirt, rust, foul taste, and odor, and a carbon clock filter (CTO) is used to reduce taste, odor, chlorine, heavy metals, and contaminants. All the three filters can hold up to maximum temperature of 52 C, with the typical lifespan between 6 and 12 months. After that, the main RO membrane is included with a maximum flow of 0.75 GPM and a maximum TDS of 2000 mg/L or more, operates at a working pressure of 0.4–0.8 MPa and has an average lifespan of 1-2 years. The RO membrane is followed by two optional additional post-treatment filters: a second carbon filter and an ultraviolet light for disinfection. All filters and membranes used in this study were commercially manufactured and obtained from established suppliers and not custom-made or laboratory fabricated. It also includes the storage tank, which is used to manage the pressure, and the pressure pump (PP) is designed in a stainless steel container with adjustable pressure (plunger pump) used to increase water pressure before entering the RO membrane with a working pressure of up to 70 psi. This pump connected with a valve for controlling the inlet pressure up to 30 psia and a gauge pressure for measuring water pressure.

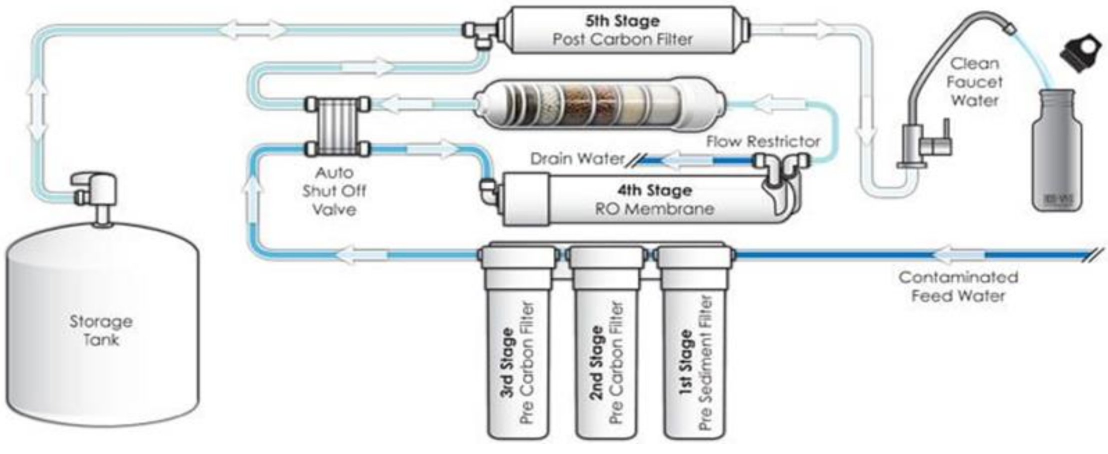


Fig. 1. General diagram of treatment process of RO system (Water filter systems, 2023).

2.2. Data collection

An experimental study was carried out to evaluate the performance of a small commercial RO unit under laboratory conditions. The study extended over a period of 60 days and was divided into two phases. Phase one (30 days): Field measurements of the total dissolved solids (TDS) in feed, permeate and concentrate water and the time required to fill the beaker were recorded for 30 days in December 2022, to assess operating conditions and efficiency of the RO unit. Water samples were collected in 150 ml plastic beakers, which were rinsed before each use to avoid contamination. These measurements were used to calculate the operating parameters of the RO unit: the discharge rates (feed (Qf), permeate (Qp), and concentrate (Qc)), Recovery ratio (R), Permeate flux (J), Salt passing (Sp) and Salt rejection (Sr), as explained in Table 1 and 2. Phase two (30 days): Concentrate water rejected from another RO unit was collected and pumped into the RO unit as feed water for 30 days at January 2023, to examine the RO performance in treating concentrate water and reducing the environmental impact. During this phase, selected water quality parameters including TDS, pH, electrical conductivity (EC), and temperature of feed, permeate, and concentrate water of the RO unit were measured using a portable multi-parameter meter (TDS/pH/EC/Temp meter). All water samples were analyzed in accordance with the standard procedures of APHA (2012). Tests were conducted under room temperature conditions in the Civil Engineering Department laboratory at the University of Baghdad.

2.3. Artificial neural network (ANN) model

Two models of ANN were developed to predict the total dissolved solids (TDS) concentration in permeate water (mg/L) and the removal efficiency of the commercial RO unit. The size of each model consisted of 30 daily measurements of the selected water quality parameters and divided into 22 for training, 6 for testing, and 2 for validation (holdout). This division is determined through trial and error to identify the split that results in the lowest testing error and a high value of the determination coefficient (R^2) which shows the ability of the ANN model for prediction. The rescaling method for data is standardization, and the activation functions were hyperbolic tangent and identity for hidden and output layers. The ANN model consists of layers of neurons such as the input, output and hidden layers. There are 11 input layers for the TDS permeate model and 12 input layers for removal efficiency model and the input variables included the water quality parameters for feed, permeate and concentrate water, while one output layer for the TDS permeate and the removal efficiency models, as presented in Fig. 2. Several factors influence the predictive performance of ANN models, including the choice of training algorithm, the number of hidden layers and nodes, and the overall network architecture. In addition, the size of the training dataset and the learning rate strongly affect model accuracy, as reflected in performance metrics such as the correlation coefficient (R^2) (Saleem et al., 2019).

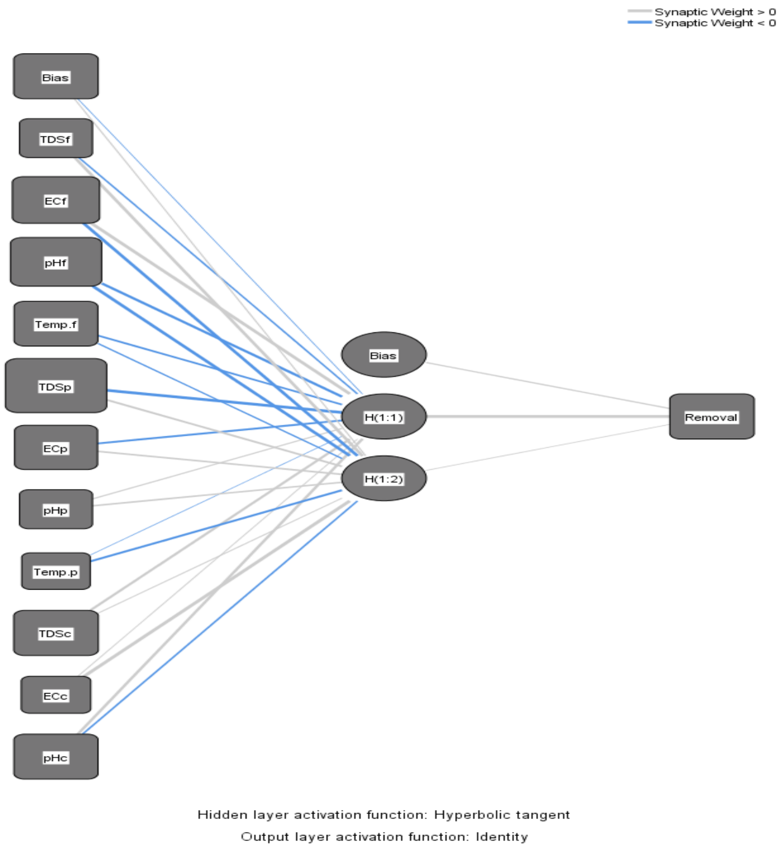


Fig. 2. ANN model with input, hidden and output layers for removal efficiency predication.

3. RESULTS AND DISCUSSION

3.1. Calculations of RO operating conditions

At phase one, the operating conditions of the RO unit were measured as shown in Table 1, through using the equations presented in Table 2 (Alonso, 2020). The salt passage refers to the amount of salt that passes through the RO unit, and it decreases as RO performance increases. The membranes may need to be cleansed or changed if there is a high salt passage (Wali et al., 2015). The opposite of salt passage is salt rejection rate (S_r), which represents the efficiency of the RO unit. A high value of salt rejection indicates great performance of the RO system. Low salt rejection may indicate that the membranes need to be cleaned or replaced. As reported by (Henkens and Smit, 1979) an RO system with effectively functioning RO membranes could eliminate 95% - 99% of the salt in the feed water. The result showed that the percentages of salt passage and salt rejection of the RO unit were 4.٦2% and 95.2%, respectively, as shown in Table 1. As a result, RO unit has a good salt rejection (95.2%) and proved to have good performance in removing salt and producing highly pure water for drinking with average TDS concentration about 15 mg/L. Fig. 3 shows the TDS concentration in the feed, permeate and concentrate water during the period of study 30 days. The result showed that the recovery rate of the RO unit was about 40% which influences salt passage and permeate flux. As the recovery rate rises, the salt concentration on the feed-concentrate side of the membrane rises, resulting in increased salt passing value and decreasing the permeate flow rate (Salinas-Rodriguez et al., 2021).

Table 1. The calculated operating conditions parameters of the RO unit.

Parameter	Value
Flow rate (Q)	Qf = 0.94 m^3 /d, Qp = 0.3٦ m^3/d, Qc = 0.58 m^3/d
Recovery ratio (R)	40 %
Permeate flux (J)	0.04143 cm/sec
Salt passing (Sp)	4.62%
Salt rejection (Sr)	95.2 %
Surface area of membrane (Am)	100.58 cm^2

Table 2. Equations for calculating Ro performance parameters (Alonso, 2020).

Parameter	Formula	Definition
Flow rate	Q = Volume/Time	The volume of water that pass over a given period
Salt passing %	Sp = TDSp / TDSf	Ratio of TDS concentration in permeate to feed water TDS concentration
Salt rejection %	Sr = 1 - Sp	Percentage of salts rejected by the RO membrane
Recovery ratio	R = Qp / Qf	Fraction of feed water converted into permeate
Permeate flux	J = Qp / Membrane Area	Flow rate of permeate per unit membrane area

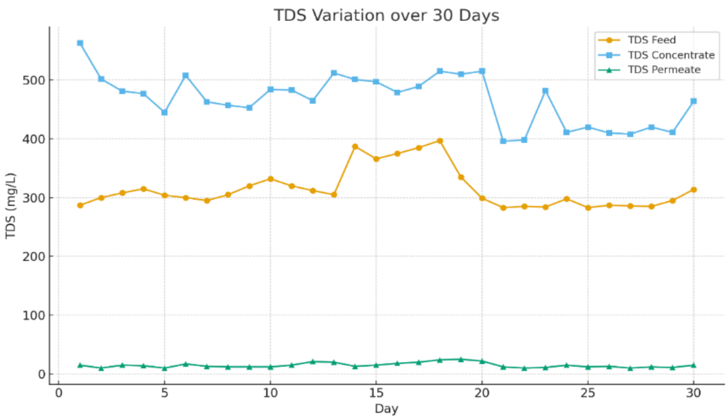


Fig. 3. TDS concentration variation over 30 days.

3.2. RO Performance in treating concentrate water

At phase two, the average values through 30 days of the selected water parameters for feed, permeate and concentrate water from the RO unit are listed in Table 3. According to the standard values of Iraqi limit and WHO (2022) Table 3 and Fig. 4, the values of TDS and EC parameters in the product water were within the allowable concentrations for Iraqi standards, while the pH value is lower than the limit. Increasing feed water pH to a range between 3 and 10 causes the permeate pH to rise , and increases the removal percentage and permeate water purity (Idrees, 2020). The results for the TDS and EC parameters agreed with the findings of these studies (Hasan and Taleb, 2020, and Yousif et al., 2022). Fig. 5 shows the removal efficiency of the most important parameters that affect the quality of water produced from the RO unit: TDS and EC were 95.7% and 95.4%, respectively. As a result, RO unit has a highly removal efficiency (95.7%) and proved to have good performance in removing salt from concentrate water and producing highly pure water for drinking with average TDS concentration about 20.5 mg/L, reducing the wastage of water and the environmental impact of disposing concentrate water.

Table 3. Average values of the selected water parameters compared to Iraqi standard and WHO values (2022).

Parameters	Unit	Feed water	Permeate water	Reject water	Removal %	Iraqi standards	WHO
TDS	mg/L	488	20.5	632	95.7	1000	1000
EC	µS/cm	1009	46.2	1358	95.4	1500	1500
pH	--	6.5	6.1	6.5	5.72	6.5-8.5	6.5-8.5
Temperature	°C	22.5	22.6	22.4	----	25	25

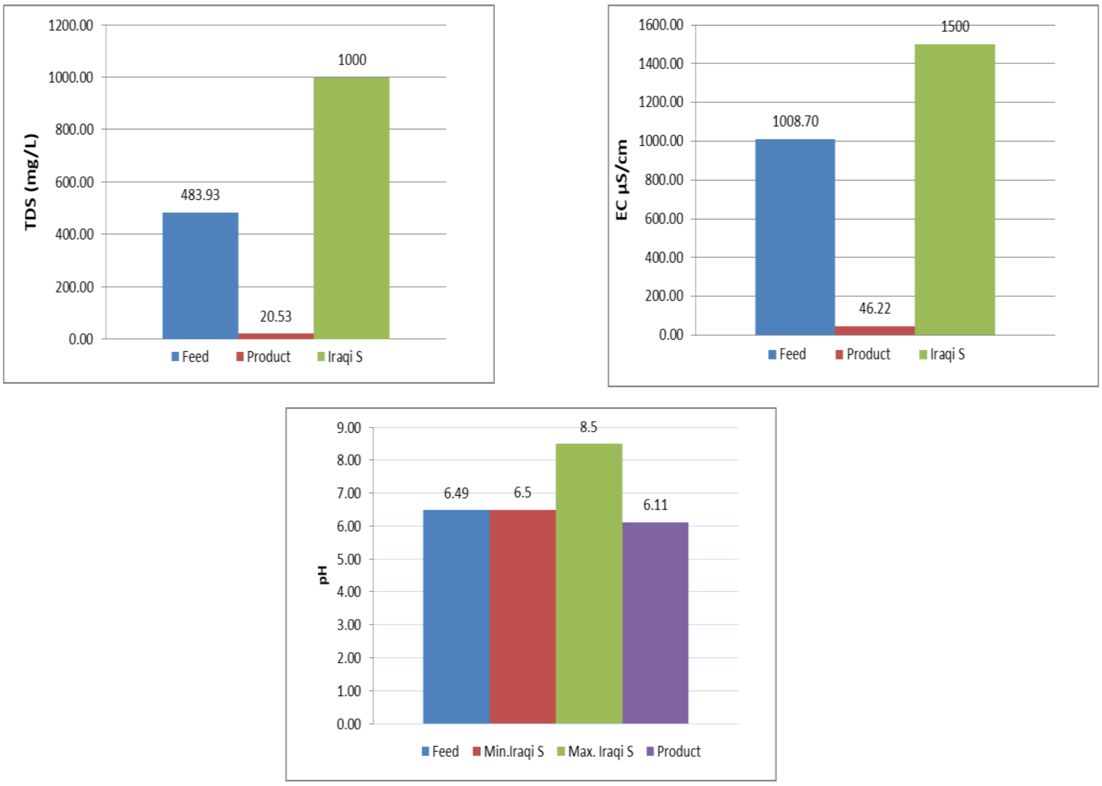


Fig. 4. Average measured values of TDS, EC and pH for feed and permeate water of RO unit compared to Iraqi standards.

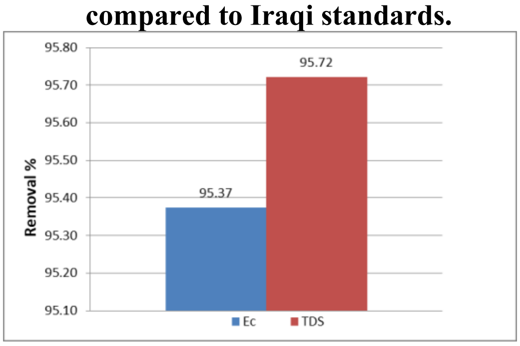


Fig. 5. The removal efficiency of TDS and EC parameters for RO unit.

3.2.1. Effect of Temperature on RO performance

This test was conducted for 30 days at January 2023 (winter season). The scatter plot was applied to the collected data to calculate the effect of temperature variation in feed water on the removal percentage of the RO unit, as shown in Fig. 6. The result showed that when the temperature increases, the removal percentage slightly decreases as shown by the trendline presented in Fig. 6, and the optimum operating temperature is 21.8°C with the highest removal percentage of about 96.9%. This result agreed with the findings presented by the researcher (Salih and Dhiaa, 2023). Also, Abdul muttaleb et al. (2014) reported that the salt rejection decreases as the feed temperature increases from 25 to 45°C, which leads to the decreased viscosity and density of the feed water, which increases the salinity of the product water and the permeation flux of the RO membrane. In addition, Yousif et al. (2022) mentioned that when the temperature of feed water rises from 5°C to 30°C, there is a constant reduction in salt removal percentage. The probability of impurities passing through the membrane pores will increase as the temperature rises, which can affect and reduce the percentage of salt rejection and increase the salinity of the produced water (Idrees, 2020).

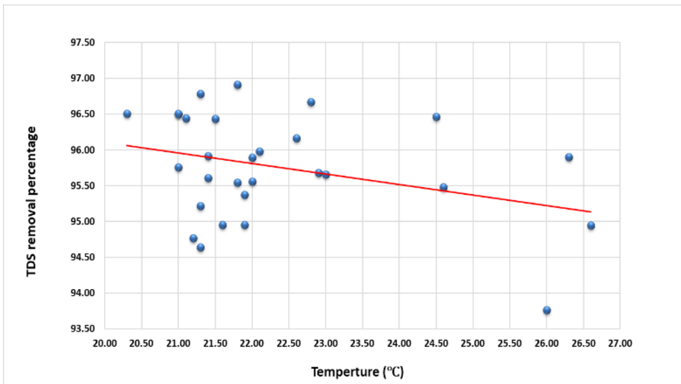
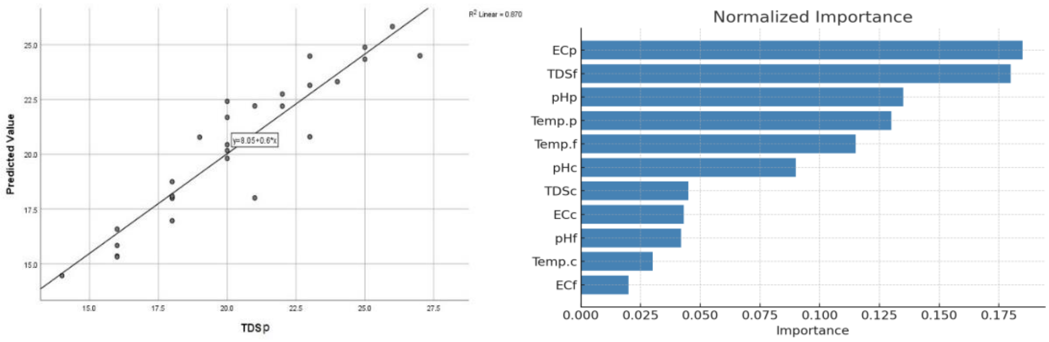


Fig.6. Feed water temperature vs the TDS removal percentage.

3.3. ANN Performances

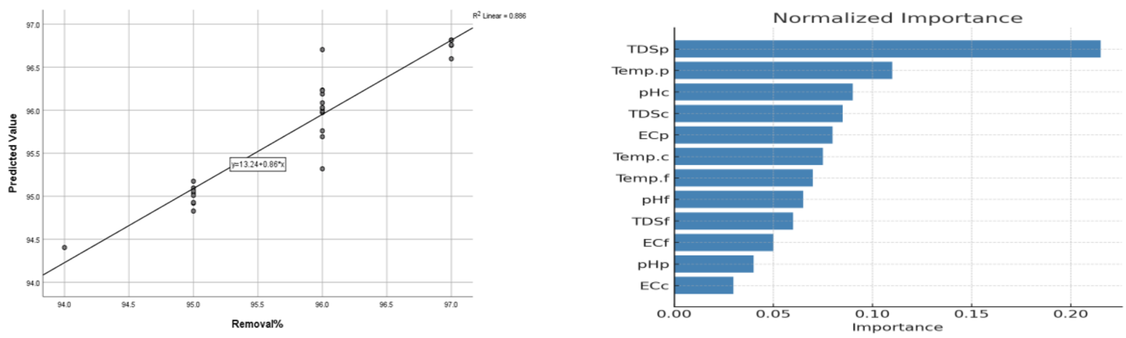
The first ANN model was employed for the input values of water quality parameters of (feed, permeate and concentrate) to estimate the output value of the dependent variable TDS permeate. Several ANN trials were performed to evaluate how different combinations of input parameters influenced prediction accuracy. The result showed that the best model was selected when using 11 input parameters as predicators giving the highest coefficient of determination (R^2= 0.870), as shown in Fig. 7-a. For this model, the most independent variables effect on the predicated TDS permeate was the electrical conductivity (EC) of permeate water (ECp) (Fig. 7-b). This suggests a high degree of predictive accuracy that is in line with the physical relationship between TDS and EC, as estimated by (Kadhim et al., 2023b). The error rate of approximately 23% reflects the variability in the dataset and the limited sample size.



(a) (b)

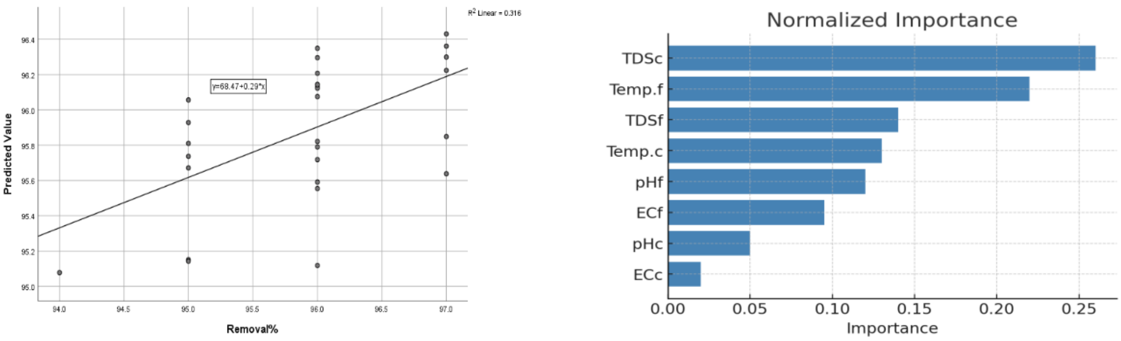
Fig.7. (a) ANN model for predicting permeate TDS values.
(b) Importance of individual input variables in predicting permeate TDS

The removal efficiency of the RO unit was predicted using the second ANN model. Several ANN trials were performed to evaluate how different combinations of input parameters (feed, concentrate, and permeate) influenced prediction accuracy. Figs. 8–11 present the results of these trials, showing both the prediction performance (coefficient of determination, R^2) and the relative importance of individual input variables. The best performing model was obtained when using concentrate and permeate water parameters (TDSc, pHc, Temp.c, ECc and TDSp, pHp, Temp.p, ECp) as predictors with 8 input layers, yielding an R^2 value of 0.902 and highlighting permeate TDSp as the most influential predictors, as shown in Fig. 11. This indicates a high level of predictive accuracy which is consistent with the physical relationship between concentrate and permeate water parameters and the salt rejection process as estimated by (Wali et al., 2015). The stronger performance of the removal efficiency model compared with the permeate TDS model (R^2 = 0.902 vs. 0.870) can be explained by the fact that removal efficiency is a derived metric that integrates multiple parameters. As a result, it exhibits stronger and more consistent correlations with the input variables, whereas permeate TDS is more sensitive to measurement variability and external fluctuations. Overall, these results suggest that ANN modeling is useful for predicting removal efficiency, as it provides a reliable indicator of RO performance under the tested operating conditions.



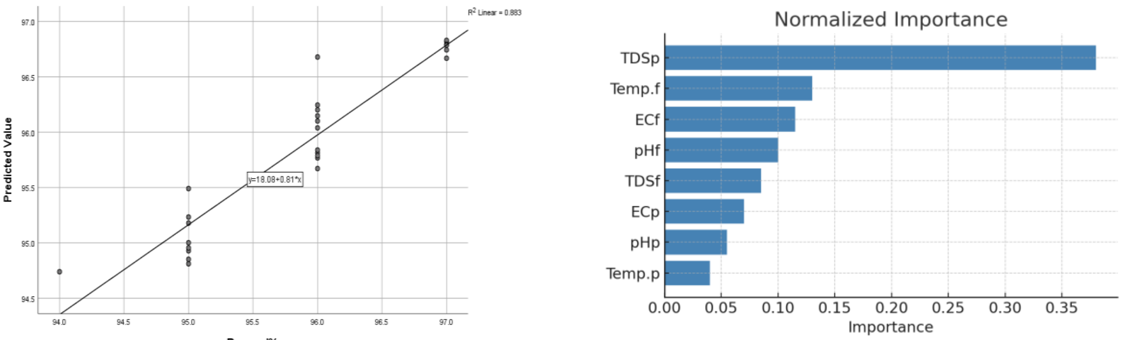
(a) (b)

Fig. 8. (a) ANN model predictions of removal efficiency using feed, concentrate, and permeate parameters as inputs (TDS, EC, pH, and temperature).
(b) Relative importance of individual input variables in predicting removal efficiency.



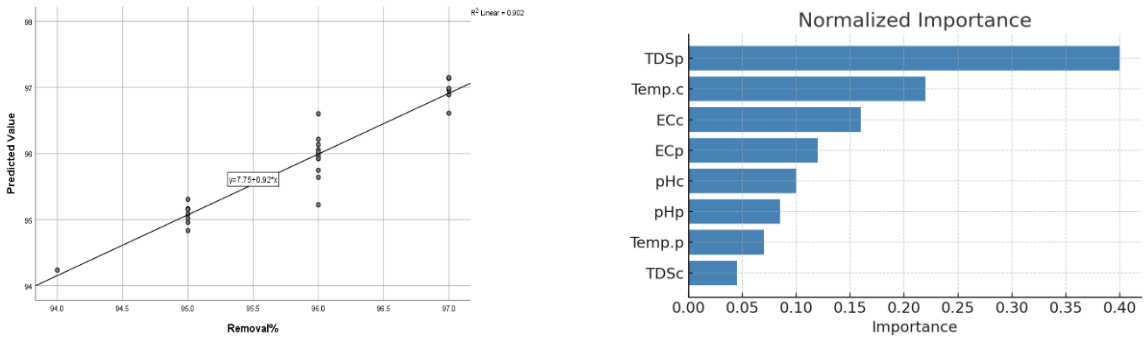
(a) **(b)**

Fig. 9. (a) ANN model predictions of removal efficiency using feed and concentrate parameters only. (b) Relative importance of input variables.



(a) **(b)**

Fig. 10. (a) ANN model predictions of removal efficiency using feed and permeate parameters only. (b) Relative importance of input variables.



(a) **(b)**

Fig. 11. (a) ANN model predictions of removal efficiency using concentrate and permeate parameters only. (b) Relative importance of input variables.

4. CONCLUSIONS

This study evaluated the performance of reverse osmosis (RO) pilot plant in treating RO concentrate for the reuse and reducing water loss and the environmental impact and developed an artificial neural network (ANN) model to predict permeate TDS and RO removal efficiency. At phase one, the RO unit has a good salt rejection (95.2%) and proved to have good performance in removing salt and producing highly pure water for drinking. At phase two, experimental measurements over 30 days showed that the RO unit achieved an average removal efficiency of TDS from concentrate water of 95.7%, with permeate water quality meeting Iraqi and WHO drinking water standards. The observed operating temperature effect indicated a slight decline in removal efficiency with increasing temperature within the limited winter dataset (20–26 °C), with the highest efficiency (96.9 %) occurring near 21.8 °C. The ANN modeling demonstrated moderate predictive ability for permeate TDS ($R^2 = 0.870$) and strong predictive ability for removal efficiency ($R^2 = 0.902$). This difference arises because removal efficiency integrates multiple operating parameters, leading to stronger correlations, while TDS is influenced by greater variability. Compared with previous ANN studies based on water treatment, the present results confirm that ANN models can be effectively applied to pilot scale RO unit, even with limited datasets, to support plant monitoring and prediction of performance. This study has limitations, including its reliance on a narrow range of operating conditions during one season, and a small dataset. Future work should expand to multi-seasonal data collection, larger datasets, and diverse RO configurations. Such research will strengthen the operational applicability of predictive models for desalination systems.

5. REFERENCES

Abbas, S.H., Khudhair, B.H. and Jaafar, M.S. (2021) 'Membrane fouling reduction for reverse osmosis system using Zeta Rod', Journal of Engineering Science and Technology, 16, pp. 1951–1961.

Abdulmuttaleb, S., Dalaf, A. and Sabri, L. (2014) 'Effect of operating conditions on reverse osmosis (RO) membrane performance', Journal of Engineering, 20(12), pp. 61–70.

Alfonso, R., Gloria, A.S., Francisco, O., Jesús, G. and Concepción, C. (2014) 'Reverse osmosis seawater desalination: Current status of membrane systems', Desalination and Water Treatment. Available at: https://doi.org/10.1080/19443994.2014.942378.

Alonso, G., del Valle, E. and Ramirez, J.R. (2020) 'Desalination plants', in Desalination in Nuclear Power Plants. pp. 31–42. Available at: https://doi.org/10.1016/b978-0-12-820021-6.00003-x

American Public Health Association, American Water Works Association and Water Environment Federation (2012) Standard methods for the examination of water and wastewater. 22nd ed. Washington, DC: American Public Health Association.

Hasan, Z.I. and Taleb, A.H. (2020) 'Assessment of the quality of drinking water for plants in the Al-Karkh, Baghdad, Iraq', Ibn AL-Haitham Journal for Pure and Applied Sciences, 33(1), pp. 1–15.

Hayder, S., Khudhair, B.H. and Jaafar, M.S. (2019) 'Water quality assessment and total dissolved solids prediction for Tigris River in Baghdad City using mathematical models', Journal of Engineering Science and Technology, 14(6), pp. 3337–3346.

Henkens, W.C.M. and Smit, J.A.M. (1979) ‘Salt rejection and flux in reverse osmosis with compactible membranes’, Desalination, 28(1), pp. 65–85.

IBM Corporation (2011) IBM SPSS Neural Networks 20: Guide. New York: IBM Software Group.

Idrees, M.F. (2020) ‘Performance analysis and treatment technologies of reverse osmosis plant – A case study’, Case Studies in Chemical and Environmental Engineering, 2, 100007. https://doi.org/10.1016/j.cscee.2020.100007.

Jamaly, S., Darwish, N., Ahmed, I. and Hasan, S.W. (2014) ‘A short review on reverse osmosis pretreatment technologies’, Desalination, 354, pp. 30–38.

Kadhim, A., Khadhair, B.H. and Jaafar, M.S. (2023b) ‘Estimate raw water salinity for the Tigris River for a long time using a mathematical model’, IOP Conference Series: Earth and Environmental Science, 1222(1), p.012037. https://doi.org/10.1088/1755-1315/1222/1/012037.

Kadhim, R.A., Khudhair, B.H. and Jaafar, M.S. (2023a) ‘Comparative study of water desalination using reverse osmosis (RO) and electro-dialysis systems (ED): Review’, Journal of Engineering, 29(4), pp. 61–77. https://doi.org/10.31026/j.eng.2023.04.04.

Katal, R., Shen, T.Y., Jafari, I., Masudy-Panah, S. and Hossein, M. (2020) ‘An overview on the treatment and management of the desalination brine solution’, in Desalination - Challenges and Opportunities. Available at: https://doi.org/10.5772/intechopen.92661.

Khan, A.A., Gaur, R.Z., Mehrotra, I., Diamantis, V., Lew, B. and Kazmi, A.A. (2014) ‘Performance assessment of different STPs based on UASB followed by aerobic post treatment systems’, Journal of Environmental Health Science and Engineering, 12(1). Available at: https://doi.org/10.1186/2052-336X-12-43.

Kress, N. (2019) Marine environmental impact of seawater desalination. In: Science, Management, and Policy. Elsevier Inc. ISBN 978-0-12-811953-2.

Lilane, A., Saifaoui, D., Hariss, S., Jenkal, H. and Chouiekh, M. (2020) ‘Modeling and simulation of the performances of the reverse osmosis membrane’, Materials Today: Proceedings, 24, pp. 114–118.

Luo, Y., Guo, W., Ngo, H.H., Nghiem, L.D., Hai, F.I., Zhang, J., Liang, S. and Wang, X.C. (2014) ‘A review on the occurrence of micropollutants in the aquatic environment and their fate and removal during wastewater treatment’, Science of The Total Environment, 473–474, pp. 619–641.https://doi.org/10.1016/j.scitotenv.2013.12.065.

Mujtaba, I. et al. (2017) ‘Desalination: Processes, technologies, and challenges’, in The Water–Food–Energy Nexus. Taylor & Francis, pp. 3–67. https://doi.org/10.1201/9781315153209-2.

Nair, M. and Kumar, D. (2013) ‘Water desalination and challenges: The Middle East perspective: A review’, Desalination and Water Treatment, 51(10–12), pp. 2030–2040.

Saleem, K., Kheioon, I. and Sultan, H. (2021) “PREDICTION OF HEAT TRANSFER CHARACTERISTICS FOR FORCED CONVECTION PIPE FLOW USING ARTIFICIAL NEURAL NETWORKS”, Kufa Journal of Engineering, 10(3), pp. 73–89. doi:10.30572/2018/KJE/100305.

Salih, M.A. and Dhiaa, A.H. (2023) “PERFORMANCE EVALUATION OF THE REVERSE OSMOSIS PILOT PLANT: USING SODIUM CHLORIDE AND MAGNESIUM CHLORIDE”, Kufa Journal of Engineering, 14(2), pp. 1–11. doi:10.30572/2018/KJE/140201.

Salinas-Rodriguez, S.G., Schippers, J. and Kennedy, M. (2021) ‘Basic principles of reverse osmosis’, in Desalination Technology. pp. 29–58. Available at: https://doi.org/10.2166/9781780409863_0029.

Wali, F., Khalil, K. and El-Dosari, A. (2015) ‘Operational performance and monitoring of a reverse osmosis desalination plant: A case study’, International Journal of Engineering and Technology, 5(6), pp. 3760–3767.

Wang, W. (2016) Research and realization of automatic control technology for marine reverse osmosis seawater desalination. PhD thesis. Zhejiang University of Technology.

Wasfy, K.I. (2017) ‘Brackish water desalination using reverse osmosis system’, Misr Journal of Agricultural Engineering, 34(4), pp. 1783–1800.

Waterfiltersystems (2023) Reverse osmosis water treatments. Waterfilters Cyprus. Available at: https://waterfilternet.com.

World Health Organization (2022) Guidelines for drinking-water quality: Fourth edition incorporating the first and second addenda. Geneva: World Health Organization. Available at: https://www.who.int/publications/i/item/9789241549950.

Yousif, Y.T., Abbas, A.A. and Yaseen, D.A. (2022) ‘Analysis and simulation performance of a reverse osmosis plant in the Al-Maqal port’, Journal of Ecological Engineering, 23(5), pp. 173–186. Available at: https://doi.org/10.12911/22998993/147343.

Zarzo, D. and Prats, D. (2018) ‘Desalination and energy consumption. What can we expect in the near future?’, Desalination, 427, pp. 1–9. Available at: https://doi.org/10.1016/j.desal.2017.10.046.

Zioui, D., Aburideh, H., Tigrine, Z., Hout, S., Abbas, M. and Merzouk, N.K. (2017) ‘Experimental study on a reverse osmosis device coupled with solar energy for water desalination’, in Proceedings of the IEEE International Renewable and Sustainable Energy Conference (IRSEC), pp. 1–5.