

Modeling and Optimization of Reverse Osmosis Plant for High Salinity Water from Shatt Al-Arab River in Southern Iraq

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Abstract

High salinity in the Shatt al-Arab River is becoming a serious issue for scientists and experts in the Basra Governorate, Iraq, and the local authorities are searching for solutions. This study aims to model and simulate the performance of the GARO2 desalination plant in the Garmatt-Ali region using Winflows 4.04 program. The high salinity of the Shatt al-Arab River elevated the salinity level of the water. The software was used to simulate the long-term operation of the GARO2 desalination plant. The results show a good agreement between the practical aspect and the modeling process, with the highest deviation being up to \pm 10%. Furthermore, Genetic Programming and Genetic Algorithms were employed to develop and analyze the objective functions were associated with the most effective factors, such as the permeate flow rate, water flux, permeate water concentration, and salt rejection. The Genetic Algorithm was used to determine the optimal values of independent variables for each objective function. The findings of this study provide valuable insights into the design and optimization of reverse osmosis desalination units used to treat brackish water from the Shatt al-Arab River in Southern Iraq, thereby enabling the development of more efficient water management options in the region.

Keywords: Desalination; Genetic Algorithm; Optimum condition; Simulation model

1. Introduction

The construction of numerous dams on the Tigris and Euphrates Rivers, mainly in Turkey, combined with unregulated water consumption in Iraq, has led to water scarcity. The salt concentration in the Shatt al-Arab River has increased significantly owing to the mixing of saline and fresh water. To address the population's need for household water (for activities such as washing, drinking, and rinsing), there is an immediate need to identify a viable substitute that offers longterm availability of safe drinking water. Of all the available alternatives, the reverse osmosis (RO) units are the most significant. However, this option is limited due to lack of research and practical knowledge regarding the elevated salt levels in the Shatt al-Arab.

Notably, the lack of research on the simulation and optimization of desalination plants in the study area motivated our research team to further explore this field, particularly due to the presence of multiple governmental and private desalination plants in the region.

Yousif *et al.* (2022) conducted a study to analyze and simulate a desalination plant in the Al Maqal Port. After conducting field and laboratory tests of permeate water samples, they found that the water was suitable for human use and met the Iraqi Standard Specifications (IRS). By calculating the R2 factor using Winflows 4.04 program, the simulation process was determined to closely match the practical results with an error rate of 17%. While the recovery rate fell within acceptable limits for brackish water, the observed relatively low salt rejection indicated potential membrane damage requiring chemical cleaning or replacement with new membranes, typically boasting a salt rejection rate exceeding 99.5%. However, this study did not simulate other variables related to the operation of desalination plants, such as the permeate flow rate, water flux, solute mass flux, and other operational parameters or water quality specifications.

Parra *et al.* (2021) presented a study that evaluated the efficiency of three different hybrid technologies for energy recovery in seawater desalination applications: reverse osmosis-pressure retarded osmosis (RO-PRO). To reduce the overall specific energy usage of the process, they discovered that by using the reverse osmosis system analysis (ROSA) software environment, the ideal RO setup and operating conditions that most closely resembled those stated in the patent were selected. They evaluated two different cases depending on the origin of the external low-salinity supply for the PRO process.

Chee *et al.* (2018) examined the operation of three pilot plants in Mallard Slough: RO1, 57 RO2, and NF3. The effectiveness of the current pilot plants in processing saltwater was verified using a simulation tool for ROSA. By specifying the system configuration and membrane details of the pilot plants, the ROSA assisted in generating operational parameters such as feed pressure, flux, recovery ratio, and permeated quality of the plants.

Mahadeva et al. (2021) developed and submitted models for artificial neural networks (ANN), particle swarm optimization-assisted ANNs (PSO-ANN), fuzzy inference systems (FIS), and adaptive neuro-fuzzy inference systems (ANFIS) with the goal of predicting the membrane performance of seawater reverse osmosis (SWRO) desalination plants. The PSO-ANN model outperformed the other simulated models (ANN, FIS, and ANFIS) in terms of the permeate flow rate and TDS with the fewest errors. Subsequent research indicated that these models could serve as valuable diagnostic tools for the development of SWRO desalination facilities, with the aim of reducing energy consumption and processing time.

This study have an aim to model and simulate the performance of a desalination plant in the Garmatt-Ali region, which is exposed to high salinity owing to the extension of the salt tongue to Shatt al-Arab, impacting the region's waters over a long period of operation. The simulation was conducted using Winflows 4.04 program to compare field and practical results with the program's outputs. Statistical analysis of the results was performed using the IBM SPSS software to determine the correlation coefficients for variables related to operating conditions and to identify the variables with the most significant influence on the objective function. The objective functions were then derived using the MATLAB R2010a, V: 7.10.0.499 Genetic Algorithm (GA) technology.

2. Methodology

This research focused on a RO laboratory plant located at the University of Basra (Garmatt-Ali Camp) in the Basra region of southern Iraq. The plant's geographical coordinates are 30°34'15.06" N and 47°44'43.5" E. Figure 1 illustrates the geographical position of the University of Basra, situated to the north of Basra city and on the western side of the Shatt al-Arab.

All details of GARO2 RO desalination plant are shown in Figure 2. GARO2 primarily consists of: 1) A water tank; 2) Feed pump; 3) Antiscalant injector; 4) pH modifier; 5) Micro cotton filter; 6) A high-pressure pump provides the necessary pressure; 7) Two vessels connected parallelly, each vessel containing three brackish water spiral-wound membranes (FilmTec Corporation BW30-400/34); 8) Cleaning water tank; 9) Cleaning water pump; 10) Permeate water tank; 11) Electrical power boards; 12) Valves. The specifications of the membranes used in GARO2, including the membrane characteristics, feed and inlet conditions, and detailed drawings of the membranes, are presented in Table 1. A high-pressure pump has the specifications shown in Table 2.



Figure 1. Location of the RO plant in Garrmat Ali- Basra Province



(1) Feed water tank;
 (2) Feed pump;
 (3) & (4) Chemical additives;
 (5) Micro cotton filter;
 (6) High-pressure pump;
 (7) 2 x 3 membranes (BW30 - 400/34);
 (8) Cleaning water tank;
 (9) Cleaning water pump;
 (10) Permeate water tank;
 (11) Electrical Power Board;
 (12) Valves

Figure 2. Flow sheet of the GARO2

From January 1 to June 30, 2022, water samples were collected and analyzed to determine the composition of the permeated, feed, and brine systems of the GARO2 RO desalination plant. Water samples were collected from three key locations within the desalination plant in triplicate.

1. Reservoir for water input

2. Infuse water tank

3. Pipe discharging brine water to sea

The water was collected in 0.5 L High Density Polyethylene bottles HDPE. Prior to sampling, the bottles were washed and rinsed multiple times with sample water to minimize contamination during long-term storage. Subsequently, the water samples were transported to the Sanitary Engineering Laboratory at the Civil Engineering Department of the University of Basrah for additional testing. The collected water samples were analyzed and assessed based on various water quality parameters.

To measure the TDS, using a HACH HQ 30D flexi conductivity meter. Before use, the device was calibrated according to the manufacturer's instructions. Electrical conductivity (EC) was determined using the same HACH HQ 30D Flexi conductivity meter. Owing to the fact that electrical conductivity is a relative measurement, the meter was calibrated using standard KCl solutions.

pH: A Lovibond SD 305 pH/ORP meter was used to determine the pH. The pH meter was calibrated with standard buffer solutions before each measurement.

The water temperature was measured while gathering samples using a Lovibond SD 305 pH/ORP 20 meter.

To ensure reliability and consistency of the results, all water samples were analyzed in triplicate. The average values of the triplicate measurements were reported for each water quality parameter. Over the research duration, the thorough characterization of the feed, permeate, and brine streams using a comprehensive sampling and analysis approach enabled the validation of the simulation model and optimization of the RO desalination process.

A water technologies and solutions program developed by the SUEZ group,

Winflows version 4.04, was the main tool used to analyze and predict the performance of the RO plant. Additionally, a Microsoft Excel Worksheet was primarily used to create and analyze graphs.

Using Winflows 4.04 for the development of desalination system designs is a quick and efficient approach. It is expected that users will be knowledgeable about the principles of RO system design and will understand the necessary performance of the system being studied (Yousif *et al.*, 2022).

The Genetic Programming of MATLAB R2010a, V: 7.10.0.499, was used to derive and analyze the objective functions associated with the most influential variables. These variables were identified by extracting the correlations for all variables using IBM SPSS software.

3. Results and Discussion

The development of efficient and sustainable RO desalination plants requires research on the modeling and optimization of RO systems. Researchers have utilized various techniques such as GA and Winflow programming tools to propose mathematical models involving mass and heat transfer, membrane solute permeability, and salt rejection.

Two approaches were employed in this study to develop and assess mathematical models for desalination processes and to determine the optimal operating conditions for maximizing the production of high-quality water.

The initial approach involved modeling and simulation using Winflows 4.04 program. The generated simulation data were then compared with the experimental data from the Garmatt-Ali RO desalination plant at the University of Basra, revealing a strong agreement between the two sets of data. While the deviation between simulation and experimental results differed across cases, it typically stayed within a \pm 10% range.

In the second approach, objective functions are generated and analyzed using GA to determine the most significant operating parameters. The correlation coefficients of all variables were obtained using the IBM SPSS software to identify the most influential parameters (independent variables) affecting the objective functions, such as permeate flux, permeate water quality, and salt rejection. The GA technique was used to optimize the values of the independent variables for each objective function. Using of the both approaches, researchers have developed accurate mathematical models and identified crucial operational conditions that can enhance the performance and efficiency of the RO desalination plants. This study will contribute to the development of efficient and sustainable RO desalination systems with long-term effectiveness.

	Product : B	W30-400/34			
Product Specific	ations				
Active Area (m ²)	37			
Permeate Flow Rate (n	n³/d) [m³/h]	40 [1.667]	40 [1.667]		
Stabilized Salt R	ej. (%)	99.5			
Operating Lin	nits				
Max. Operating	Temp.	45 °C			
Max. Operating	Press.	41 bar			
Maximum Pressure I	Drop (bar)	1.0			
pH Range, Continuou	s Operation	2-11			
pH Range, Short-Term C	leaning (mg/l)	1-13	1-13		
Maximum Feed Silt D	ensity Index	5	5		
Free Chlorine Tolera	nce (ppm)	< 0.1			
f france brane hit (mm)	А	40.0 (1,016)			
	В	1.125 (29.0)			
o U bhes	С	7.9 (201)			
Di M Inc	D	-			
B DIA	Fiberglass Outer Wrap		C DIA		
	DW/	30 400/34			
	D 111				

 Table 1. Specifications and operating conditions of the Plants Membrane Elements

 Table 2. Characteristics of GARO2 High-Pressure Pump HPP

Adjective	Specification		
Brand	Lowara SV-F		
Туре	10SV02F0156/M		
Pressure bar	25		
Flow l/min	40 - 143		
Flow m ³ /h	6 - 17		
Number of Impellers	2		
Motor	1x 230V		
Power kW	1,5		
Temp. max °C	40		

3.1 First Methodology: Modeling and Simulation

Water Flux (Jw):

This study employed two methodologies. The first methodology involved modeling and simulation using Winflows 4.04 program. It is noteworthy that some of the deviation percentages were negative, indicating that the Winflows programming results had higher than the experimental values. Therefore, the absolute values were used to determine the maximum and minimum deviations. The key findings are summarized as follows:

Permeate Flow Rate (Qp):

Based on Figure 3, the maximum absolute deviation was 8.13% in June 2022, whereas the minimum absolute deviation was 3.23% in January 2022. Therefore, the simulated Qp ranged from $\pm 3.23\%$ to $\pm 8.13\%$ of the experimental Qp.

The maximum deviation was 8.13%on June 18, 2022 (Figure 5). A minimum deviation of 3.23% was observed on January 3, 2022 (Figure 4), which is consistent with the experimental data. Our model predicted a deviation range of $\pm 3.23\%$ to $\pm 8.13\%$ from the experimental measurements of water flux.

Solute Mass Flux (Js):

The smallest deviation of 0.08% was observed on February 7, 2022, whereas the largest deviation of 27.33% occurred on March 17, 2002 (Figure 5). All the simulated solute mass flux values deviated from the experimental data, ranging from 0.08% to 27.33%.



Figure 3. Comparing the permeate flow rate between in Experimental and Winflows 4.04 programming results, and the percentage of deviation



Figure 4. Comparing the water flux between the experimental and Winflows 4.04 programming results, and the percentage of deviation



Figure 5. Comparing the mass flux of solute between the experimental and Winflows 4.04 programming results, and the percentage of deviation



Figure 6. Comparing the Feed Pressure Pf between the experimental and Winflows 4.04 programming results, and the deviation percentage



Figure 7. Comparing the Net Driving Pressure NDP between the experimental and Winflows 4.04 programming results, and the deviation percentage

Feed Pressure (Pf):

Feed pressure and Net Driving Pressure (NDP) had a maximum absolute deviation of 5.31% on June 26, 2022, and a minimum of 3.7% on January 2, 2022, for Pf. For NDP, the maximum absolute deviation was 8.13% on June 18, 2022, and the minimum was 3.23% on January 3, 2022 (Figures 6 and 7). The simulated Pf and NDP values deviated

by 3.7% to 8.13% from the experimental measurements.

Concentrations of permeate water (Cp):

Concentration of permeate and brine water (Cc): The maximum deviation for Cp was 23.3% on March 17, 2022, while the minimum deviation was 3.7% on January 29, 2022. Regarding Cc, the maximum deviation was 20.28% on June 4, 2022, with a minimum

of 0.36% on January 30, 2022 (Figure 8 and 9). It is evident that the simulated Cp and Cc concentrations exhibited a deviation range of 0.36% - 23.3% compared with the experimental values.

Largest deviation percentage of the calculated mass transfer coefficient (Kcp):

From the experimental correlations using the average value of ΔE was 10% on June 4, 2022, and the smallest was 0.26% on January 3, 2022, respectively (Figure 10). This indicated that the simulated Kcp values obtained for CP were very close to the correlations within 0.26% to 10%.



Figure 8. Comparing the Permeate Water Concentration Cp between the experimental and Winflows 4.04 programming results, and the deviation percentage



Figure 9. Comparing the Brine Water Concentration Cc between the experimental and Winflows 4.04 programming results, and the deviation percentage



Figure 10. Comparing the Concentration polarization mass transfer coefficient Kcp between the experimental and Wnflows 4.04 programming results, and the deviation percentage

Concentration Polarization Factor (β):

In June 2022, the maximum highest absolute deviation percentage value for β was 1.38% (Figure 11), and the minimum was 0.39% on January 3, 2022. This indicates that the simulated values of the concentration polarization factor deviated within the range of 0.39% to 1.38% when compared to the experimental data.

Concentration Polarization (Cm):

The maximum percentage error observed was 9.43% on June 4, 2022, and the minimum was 0.19% on February 1, 2022 (Figure 12). This indicates that the Cm simulations were within the range of 0.19% - 9.43% of the experimental measurements.

The maximum absolute deviation percentage for R% was observed on March 17, 2022 (0.79%), whereas the minimum was observed on January 29, 2022 was 0.01% (Figure 13). It is evident that the simulated R% values closely aligned with the experimental R% values, with deviations ranging from 0.01% to 0.79%.

Table 3 summarizes the deviation percentages between the experiments and simulation conducted using Winflows 4.04. The findings suggest a strong overall agreement between the simulation and experimental results, with the majority of deviation percentages falling within the range of $\pm 10\%$.

RO is a highly effective separation technique that is widely used in the industrial sector. To optimize system performance, the selection of the optimal set of operating parameters is usually required. GAs are faster and more efficient than conventional gradient-based optimization techniques (Murthy *et al.*, 2006).



Figure 11. Comparing the Concentration polarization Factor β between the experimental and Wnflows 4.04 programming results, and the deviation percentage



Figure 12. Comparing the Concentration polarization Cm between the experimental and Wnflows 4.04 programming results, and the deviation percentage

The concepts of GA, which are search tactics based on theories of natural evolution, are analogous to natural behavior (Gen et al., 2000). The main principle of GA is to start with a population of randomly dispersed initial solution points across the optimized space. Subsequently, the solutions are iteratively refined using crossover, mutation, and reproduction/selection processes until the intended stopping criterion is satisfied (Djebedjian et al., 2008). Genetic Programming was used to derive and analyze the objective functions, as shown in Figure 14. These functions are associated with the most significant variables identified by analyzing the correlations among all variables using the IBM SPSS software, as elaborated in the subsequent paragraph.

To deploy the objective function variables in the optimization process, this study utilizes an extensive optimization method involving GA. Initially, to identify the key variables influencing desalination plant operation, fundamental variables were extracted using the SPSS software. Correlation coefficients were calculated for each variable and those with coefficients greater than 0.5 were selected. Subsequently, objective functions were developed for optimization to determine the optimal values of the variables associated with these functions. This study focused on four target variables: the permeate flow rate (Qp), water flux (Jw), permeate concentration (Cp), and salt rejection (R%). Through Genetic Programming, specific objective functions were derived for each target variable to minimize the expected error rate.

By organizing the tables in Excel, we grouped the operating conditions obtained by the objective function and the most influential independent variables, along with the maximum, minimum, and boundary



Figure 13. Comparing the Salt Rejection R% between the experimental and Wnflows 4.04 programming results, and the deviation percentage

Variables	The State	Date	% Dev.	Variables	The State	Date	% Dev.
Qp	Max.	18-Jun	8.13	Cc	Max.	4-June	20.28
	Min.	3-Jan	3.23		Min.	30-Jan	0.36
Jw m	Max.	18-Jun	8.13	Кср	Max.	4-June	1.00
	Min.	3-Jan	3.23		Min.	3-Jan	0.26
Js	Max.	17-March	27.33	ß	Max.	4-June	1.38
	Min.	7-Feb	0.08		Min.	3-Jan	0.39
Pf -	Max.	26-June	5.31	Cm	Max.	4-June	9.43
	Min.	2-Jan	3.70		Min.	1-Feb	0.19
NDP	Max.	18-June	8.13	R%	Max.	17-March	0.79
	Min.	3-Jan	3.23		Min.	29-Jan	0.01
Ср	Max.	17-March	23.3				
	Min.	29-Jan	3.70				

Table 3. Summary of comparison of Deviation Percentage for experimental work and Winflows 4.04

Note: Second Methodology: Optimization by Genetic Algorithm



Figure 14. The objective functions and the variables with a higher correlation coefficient



Figure 15. Main code for maximizing the fitness function

conditions. Subsequently, a MATLAB GA program was used to validate the objective functions developed in-house. The experimental data from GARO2 were then compared with the calculated results to confirm the validity of the derived functions (Figure 15).

Additional refinement of the optimization procedure involved further repetition of the GA optimization step without constraints other than those imposed by the bounds on the variables. Subsequently, we wrote the main MATLAB function and summarized the different codes used. Finally, we executed the GA optimization procedure and obtained optimal values for the independent variables.

The utilization of GA as a comprehensive optimization procedure has facilitated the determination of the dominant constituents and the generation of precise and tangible objective functions that portray the performance of the desalination process, providing essential guidance for determining the optimal operational values.

4. Conclusion

The high salinity of the Shatt al-Arab River poses a significant challenge to the operation of RO desalination plants in the Garmatt-Ali region of Basra, Iraq. This study are employed an integrated approach to model and optimize its performance.

The initial process involved building and simulating using Winflows 4.04 software. The simulated results were compared with the experimental data obtained from the GARO2 desalination plant to analyze the percentage deviation of various performance parameters. These parameters include the permeate flow rate, water flux, solute mass flux, feed pressure, net driving pressure, permeate water concentration, permeate mass concentration, brine water concentration, brine mass concentration, concentration polarization mass transfer coefficient (Cp), concentration polarization factor (gamma), and salt rejection (R). The accuracy of the simulation results was verified by comparing them with the experimental data, with a maximum deviation of $\pm 10\%$.

This study focused on the using GA techniques to optimize RO systems. Variables that exerted the greatest influence on the objective functions, such as the permeate flow rate (Qp), water flux (Jw), permeate water concentration (Cp), and salt rejection (R%), were identified using IBM SPSS software. Using Genetic Programming, objective functions were developed for key performance indicators. Subsequently, GA was used to determine the optimal values of the independent variables for each objective function.

For the Qp objective function, the optimal values of T (Temperature), r% (Recovery rate), Sc (Schmidt number), and Kcp (Concentration polarization mass transfer coefficient) were determined to be 20.519°C, 45.01%, 572.6 m²/s, and 2.456×10^{-5} m/s, respectively. Similarly, for Cp as the objective function, the optimal values of feed concentration (Cf), brine concentration (Cc), feed pressure (Pf), and net driving pressure (NDP) were 1063 mg/L, 1491 mg/L, 21.938 bar, and 16.197 bar, respectively. In contrast, Cm (Concentration polarization), R% (Salt rejection), P% (Permeate percentage), and Js (Mass flux of solute) were determined to be 1436.16 mg/L, 99.4%, 0.5%, and 1315.3 mg/m².h, respectively.

The results of this study present significant conclusions regarding the modeling and optimization of RO desalination plants for treating highly saline water from the Shatt al-Arab River in southern Iraq. The developed models and optimization algorithms can assist in formulating effective and economical water management plans for the district. The findings of this investigation provide valuable insights into the modeling and optimization of RO desalination plants that treat highly saline water from the Shatt al-Arab in southern Iraq, shedding light on opportunities for successful water management in the region.

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