OPTIMIZATION OF REVERSE OSMOSIS DESALINATION SYSTEM USING GENETIC ALGORITHMS TECHNIQUE

Berge Djebedjian *, Helmy Gad *, Ibrahim Khaled **, and Magdy Abou Rayan *

* Mechanical Power Engineering Department, Faculty of Engineering, Mansoura University, El-Mansoura 35516, Egypt
E-mails: bergedje@mans.edu.eg, he_gad@yahoo.com, mrayan@mans.edu.eg
** Sinai Development Authority, Egypt

ABSTRACT

In this paper, a methodology is developed for optimization of the reverse osmosis (RO) desalination system performance. The solution-diffusion model is used for the modeling. The optimization of RO systems is achieved by the genetic algorithms (GA) technique. The objective function is taken as the maximization of permeate volumetric flow rate. The optimization problem is to find the best pressure difference across the membrane which maximizes permeate volumetric flow rate and fulfill the permeate concentration constraint. The used constraint is that permeate concentration to be less than a desired value. A computer program was written in FORTRAN, GARO program (Genetic Algorithm Reverse Osmosis) to include the methodology. A binary-coded micro-genetic algorithm was linked with the equations describing the RO system performance. The methodology was tested on a real RO desalination plant in Nuweiba City, Egypt. Results from application of the GARO program on this plant have shown that the relationship between the operating pressure difference across membrane and permeate volumetric flow rate is approximately linear. The permeate concentration decreases with the increase in volumetric flow rate and the membrane pressure difference. The theoretical results obtained are seen to be in a good agreement with that experimentally obtained from the optimization program especially at higher flow rates.

Keywords: Desalination, Reverse osmosis, Optimization, Genetic algorithm.

NOMENCLATURE

- \( a \) permeability coefficient for water (m/h.bar)
- \( a_{SP} \) specific surface area of the spacer (m\(^{-1}\))
- \( A \) active area of membrane (m\(^2\))
- \( b \) permeability coefficient for salt (m/h)
- \( b_s \) osmotic coefficient (m\(^3\).bar/kg)
- \( B \) total width of the membrane leaves in their unwound state (m)
- \( C_b \) salt concentration in the high-pressure side (kg/m\(^3\))
\( C_p \) concentration of the permeate (kg/m\(^3\))

\( C_{p,d} \) desired permeate concentration (kg/m\(^3\))

\( C_{pen} \) penalty function constant

\( C_{wall} \) concentration at the membrane wall (kg/m\(^3\))

\( d \) channel height (m)

\( d_h \) hydraulic diameter of channel (m)

\( d_{SP} \) spacer thickness (m)

\( D_{AB} \) mass diffusivity of salt (A) through water (B) (m\(^2\)/h)

\( f(x) \) fitness function

\( F(x) \) objective function

\( J_w \) volumetric flux of water (m/h)

\( J_s \) mass flux of salt (kg/m\(^2\).h)

\( k_s \) mass transfer coefficient of salt in feed side (m/h)

\( P \) pressure (bar)

\( Pen \) penalty function

\( Q_f \) feed water volumetric flow rate (m\(^3\)/h)

\( Q_w \) permeate volumetric flow rate (m\(^3\)/h)

\( Re \) Reynolds number, \( d_h v / \nu \)

\( Sc \) Schmidt number, \( \nu / D_{AB} \)

\( Sh \) Sherwood number, \( k_s d_h / D_{AB} \)

\( T \) temperature (°C)

\( v \) velocity of water in feed channel (m/h)

\( Z \) objective function

**Subscripts**

\( b \) brine

\( f \) feed

\( o \) outlet

\( p \) permeate

**Greek symbols**

\( \Delta \) difference

\( \varepsilon \) void fraction (bulk porosity or voidage)

\( \mu \) dynamic viscosity of salt solution (Pa.s)

\( \nu \) kinematic viscosity of salt solution (m\(^2\)/h)

\( \pi \) osmotic pressure (bar)

\( \rho \) density of seawater (kg/m\(^3\))

**ABBREVIATIONS**

GARO Genetic Algorithm Reverse Osmosis program

MSF Multi Stage Flash

pH Acidity Measure

RO Reverse Osmosis
INTRODUCTION

Genetic Algorithms (GAs) are stochastic search methods that mimic the process of natural biological evolution, Holland (1975). GAs operates on a population of potential solutions applying the principle of survival of the fittest to produce better approximations to a solution. In the field of chemical engineering design, GAs has been applied for different operations.

Optimization tools have been applied to RO and hybrid desalination plants in the following areas:

1. Prediction and optimization of RO plant performance. These include multistage RO systems (e.g. Marcovecchio et al., 2005 and Lu et al., 2007).
2. Optimization of hybrid desalination processes (e.g. Helal et al., 2003, 2004; Mohamed, 2006 and Cardona et al., 2007).

Results of these applications would be better design, improved efficiency and increased operational safety. Table 1 summarizes the papers that deal with the optimization of RO systems and the optimization technique used in the study.

Table 1 Optimization of the RO system

<table>
<thead>
<tr>
<th>Authors</th>
<th>Year</th>
<th>Optimization method</th>
</tr>
</thead>
<tbody>
<tr>
<td>Poullikkas</td>
<td>2001</td>
<td>GA</td>
</tr>
<tr>
<td>Villafafila and Mujtabab</td>
<td>2003</td>
<td>SQP</td>
</tr>
<tr>
<td>Abbas</td>
<td>2004</td>
<td>-</td>
</tr>
<tr>
<td>Guria et al.</td>
<td>2005</td>
<td>NSGA</td>
</tr>
<tr>
<td>Murthy and Vengal</td>
<td>2006</td>
<td>GA</td>
</tr>
<tr>
<td>Lu et al.</td>
<td>2006</td>
<td>MINLP</td>
</tr>
</tbody>
</table>

Poullikkas (2001) investigated an optimization by Genetic Algorithm for the calculation of water unit cost. Various RO candidate schemes were developed. Such an algorithm may be used for evaluation purposes when many RO candidate schemes are taken into account. The applicability of the method was demonstrated on an example in which six RO candidate schemes were examined.

Villafafila and Mujtabab (2003) studied the seawater RO desalination process. First, a model for the process was developed. Sensitivity of different operating parameters (feed flow rate, feed pressure) and design parameters (internal diameter, total number of tubes) on the recovery ratio were studied via repetitive simulation. Finally, an optimization framework for the process was developed so as to maximize the recovery ratio or a profit function using different energy recovery devices subject to general constraints. The optimal operating and design parameters were determined by
using an efficient successive quadratic programming (SQP) based method. The optimal values for the decision variables depended on the constraints introduced, and were also sensitive to variations in water and energy prices, as well as feed concentration. The use of the emerging energy recovery devices was widely justified, reporting much higher reductions in operating costs than the traditional technology used for this purpose. By using a pressure exchanger device, it was possible to reduce energy consumption by up to 50%.

Abbas (2004) studied the effects of the arrangement of membrane modules; the operating pressure and the feed flow rate on the performance of simulated medium-size brackish water RO desalination plant. The single-stage configuration in which all pressure vessels are arranged in parallel was found to yield the best results in terms of the production rate and product quality. At low and moderate operating pressures and feed rates, increasing both operating variables will result in higher water recovery and salt rejection. However, high operating pressures led to a deterioration of the quality of the product whereas high flow feed rates, contrary to the expectation; resulted in a reduction in the production rate.

Guria et al. (2005) studied the multi-objective optimization using GA for desalination of brackish and sea water using spiral wound or tubular modules. Few sample optimization problems involving two and three objective functions were solved, both for the operation of an existing plant, as well as, for the design of new plants. The possible objective functions were: maximize the permeate flow, minimize the operation cost and minimize the permeate concentration. The operating pressure difference across the membrane was the only important decision variable for an existing unit. In contrast, for a new plant, operating pressure difference, the active area of the membrane, the membrane to be used (characterized by the permeability coefficients for salt and water), and the type of module to be used (spiral wound/tubular, as characterized by the mass transfer coefficient on the feed-side) were the important decision variables. Sets of non-dominated solutions were obtained for the problems studied. The binary coded elitist non-dominated sorting genetic algorithm (NSGA-II) was used to obtain the solutions. It was observed that for maximum permeate flow, the permeability of both the salt and the water should be the highest for those cases studied where there was a constraint on the permeate concentration. If one of the objective functions was to minimize the permeate concentration, the optimum permeability of salt was shifted towards its lower limit. The membrane area was the most important decision variable in designing a spiral wound module for desalination of brackish water as well as seawater, whereas operating pressure difference was the most important decision variable in designing a tubular module for the desalination of brackish water (where the quality of the permeate was of prime importance).

Murthy and Vengal (2006) optimized the performance of RO system with a cellulose acetate membrane to separate NaCl-Water system using Genetic Algorithm (GA). The optimization problem was to maximize the observed rejection of the solute by varying the feed flow rate and overall permeate flux across the membrane for a
constant feed concentration. They used the Spiegler-Kedem transport model for RO system. It was found that the GA converged rapidly to the optimal solution at the 8th generation. The effect of varying GA parameters like size of population, crossover probability, and mutation probability on the result was also studied. It was also seen that varying the computational parameters significantly affected the results.

Lu et al. (2006) presented a systematic methodology for the optimal design of RO desalination system which consider membrane module cleaning and replacing. The design task was formulated as a mixed-integer non-linear programming (MINLP) which minimizes the total annualized cost while subject to the thermodynamics, modeling, economic, environmental, and feasibility constraints. The optimum RO maintenance schedule was also determined in the design stage. The effectiveness of this design methodology was demonstrated by solving a case study. This work used just a segment of system capital and operating cost.

The previous literature review demonstrates the suitability of the GA as an optimization technique to handle RO desalination systems to optimize the objective function (cost, salt concentration … etc.).

The objectives of this study is to develop a software to perform the modeling and the optimization of RO desalination systems, apply it to a large-scale commercial reverse osmosis desalination plant and examine the capabilities of the developed software in a real and large plant.

**SOLUTION-DIFFUSION MODEL**

In the solution-diffusion model (Lonsdale et al., 1965) the solute and the solvent are assumed to dissolve in the homogeneous non porous surface layer of the membrane and then are transported by diffusion under the chemical potential gradient in an uncoupled manner. The solvent (water) flux $J_w$ is defined as the volume of water passing through a unit area of the membrane. The water flux, $J_w (= Q_w/A)$, and the solute flux, $J_s$ according to solute diffusion transport mechanism are given by, (Lonsdale et al., 1965; Rautenbach, 1986, Sherwood et al., 1967 and Soltanieh and Gill, 1981) as,

$$J_w = a(\Delta P - \Delta \pi)$$  \[1\]

$$J_s = b(C_{wall} - C_p)$$  \[2\]

where $\Delta P (= P_b - P_p)$ is the applied pressure difference across the membrane, $P_b$ the pressure in the bulk solution at the high pressure side and $P_p$ is the pressure in the permeate side of the membrane. $\Delta \pi$ is the osmotic pressure difference of solute across the membrane. $C_{wall}$ is the solute concentration at the membrane surface, $C_p$ is the permeate side solute concentration and Constants $a$ and $b$ are the solvent (membrane) and the solute (salt) permeability coefficients respectively. The solute concentration
at the membrane surface is usually greater than that in the bulk solution due to polarization effects. As water flows through the membrane and salts are rejected by the membrane, a boundary layer with a higher salt concentration is formed near the membrane surface. This increase in salt concentration at membrane surface is called concentration polarization and leads to serious problems during membrane operation as it increases the overall resistance to solvent flux (Matthiasson and Sivik, 1980 and Potts et al., 1981). In the presence of concentration polarization, the steady-state water flow rate, $J_w$ is given by,

$$J_w = k_s \ln \frac{C_{wall} - C_p}{C_b - C_p}$$

where $C_b$ is the feed side bulk solute concentration.

Combining Equations (1) and (3) to eliminate $C_{wall}$, the values $J_w$ and $C_p$ can be finally obtained (Rautenbach, 1986) as,

$$J_w = a \left[ \Delta P - b_\pi \left( C_b - bC_b \exp \left( \frac{J_w}{k_s} \right) \right) \exp \left( \frac{J_w}{k_s} \right) \right]$$

and

$$C_p = C_p - \frac{bC_b}{b + J_w \exp \left( - \frac{J_w}{k_s} \right)}$$

The osmotic coefficient $b_\pi$ can be estimated using:

$$b_\pi = \frac{\pi}{C}$$

where $C$ is the concentration of all constituents in the solution, (in kg/m$^3$) and $\pi$ is the osmotic pressure (in bars) obtained from the data given by Sourirajan (1970) for the NaCl–H$_2$O solution at 25°C (concentration range: 0 - 49.95 kg/m$^3$) and is correlated as,

$$\pi = 0.7949C - 0.0021C^2 + 7.0 \times 10^{-5}C^3 - 6.0 \times 10^{-7}C^4$$

Equation (4) is an implicit nonlinear algebraic equation that can be solved numerically by the secant method to give $J_w$ for a set of values of $C_b, T, a, b, k_s, b_\pi$ and $\Delta P$. The value of $C_p$ can then be evaluated using Eq. (5).

The mass transfer coefficient can be expressed in an empirical Sherwood relationship taking into account the flow conditions (expressed in the Reynolds number, Re), the nature of the feed solution (expressed by the Schmidt number, Sc) and the geometry
of the membrane system. For a spiral-type RO element designated TORAY SU-820, which is in the case study, the Sherwood relationship is given by Taniguchi et al. (2001) as,

\[
Sh = 0.08 \ Re^{0.875} \ Sc^{0.25}
\]  

(8)

where the Sherwood, Reynolds and Schmidt numbers are defined as,

\[
Sh = \frac{k_i \ d_h}{D_{AB}}, \quad Re = \frac{d_h \ v}{\nu} \quad \text{and} \quad Sc = \frac{\nu}{D_{AB}}
\]  

(9)

where \(d_h\) is the hydraulic diameter of the membrane channel, \(D_{AB}\) is the diffusion coefficient, \(v\) is the characteristic velocity and \(\nu\) is the kinematic viscosity.

For seawater, \(D_{AB}, \mu \) and \(\rho\) (Sekino, 1994; Taniguchi and Kimura, 2000; Taniguchi et al., 2001) can be estimated from the following equations:

\[
D_{AB} = 6.725 \times 10^{-6} \ exp \left(0.1546 \times 10^{-3} \ C - \frac{2513}{273.15 + T} \right)
\]  

(10)

\[
\mu = 1.234 \times 10^{-6} \ exp \left(0.00212C + \frac{1965}{273.15 + T} \right)
\]  

(11)

and

\[
\rho = 498.4 m + \sqrt{248400m^2 + 752.4mC}
\]  

(12)

where:

\[
m = 1.0069 - 2.757 \times 10^{-4}\ T
\]  

(13)

The hydraulic diameter, \(d_h\), is given by Schock and Miquel, 1987; Van Gauwbergen and Baeyens, 2000 as,

\[
d_h = \frac{4 \ \varepsilon}{\frac{2}{d} + (1 - \varepsilon) a_{sp}}
\]  

(14)

where \(\varepsilon\) is the void fraction (bulk porosity or voidage), \(d\) is the channel height, and \(a_{sp}\) is the specific surface area of the spacer, i.e. the ratio of its surface area to its volume. It is given by: \(a_{sp} = 8 / d_{sp}\), where \(d_{sp}\) is the spacer thickness.
For a flow $Q$ through the spacer filled channel, the velocity is defined by,

$$v = \frac{Q}{B d \varepsilon}$$

(15)

Where, $d$ is approximated by the spacer thickness $d_{sp}$. The width $B$ should be taken as the total length of the membrane leaves in their unwound state.

Normally, the permeate spacer has a significantly lower porosity than the concentrate spacer. For the common concentrate spacers, the filament is approximately 0.3 - 0.4 mm thick. The voidage $\varepsilon$ value is approximated by 0.9.

**OPTIMIZATION TECHNIQUE**

The present study aims to optimize the performance of an existing RO desalination system using the GAs technique and produce the best operating pressure difference across membrane $\Delta P$ which maximizes permeate volumetric flow rate $Q_w$ and fulfill the permeate concentration constraint $C_{p,d_i}$.

For a given RO system layout (number of channels, membrane area, ... etc.), the single objective function $Z$ to be maximized is:

$$Z = Q_w$$

(16)

Optimization of an existing RO system is a constrained optimization problem. The constraint used in such system is given as:

$$C_p \leq C_{p,d_i}$$

(17)

The bounds on $\Delta P$ are specified as follows:

$$\Delta P_{\text{min}} \leq \Delta P \leq \Delta P_{\text{max}}$$

(18)

where, $\Delta P_{\text{min}}$ and $\Delta P_{\text{max}}$ are the minimum and maximum allowable pressure differences across the membrane.

In optimization techniques, external penalty functions have been used to convert a constrained problem into an unconstrained problem. Therefore, for the RO system optimization, the objective function $Z$ is given as:

$$Z = Q_w - Pen$$

(19)
where, \( Pen \) is the penalty subtracted form the objective function.

The penalty function is written as:

\[
Pen = C_{pen} \left( \frac{C_p}{C_{p,d}} - 1 \right)
\]  

(20)

where, \( C_{pen} \) is the penalty function constant and is chosen as big as 100,000.

Therefore, the objective function can be calculated from:

\[
Z = \begin{cases} 
Q_w & \text{if } C_p \leq C_{p,d} \\
Q_w - C_{pen} \left( \frac{C_p}{C_{p,d}} - 1 \right) & \text{otherwise}
\end{cases}
\]  

(21)

The penalty function is applied when the permeate concentration is not less than the desired permeate concentration.

**GARO PROGRAM**

The numerical study is concerned with writing a computer program GARO (Genetic Algorithms Reverse Osmosis) which performs the following two roles individually:

1- Simulation of a reverse osmosis system.
2- Optimization of the RO system.

The GARO is a single objective optimization program. The design of this program depends on two main techniques:

1- Genetic algorithm technique to produce the optimal pressure difference across the membrane. The used GA source code in this study is (FORTRAN GA version 1.7a) after minor modifications that written by Carroll (1996, 2001).

2- Modeling equations that simulate the RO systems and producing is performance. The secant method is used for solving the permeate flux, \( J_w \), Eq. (4).

A brief description of the procedure used in GARO program is given in the following sections.
GENETIC ALGORITHMS

Genetic algorithms are search techniques based on the concepts of natural evolution and thus their principles are directly analogous to natural behavior, Gen and Cheng (2000). The brief idea of GA is to select population of initial solution points scattered randomly in the optimized space, and then converge to better solutions by applying in iterative manner the following three processes reproduction/selection, crossover and mutation, until a desired criteria for stopping is achieved. In this study the micro-Genetic Algorithm (μGA) is used. It is a "small population" Genetic Algorithm (GA). In contrast to the more classical Simple Genetic Algorithm (SGA), which requires a large number of individuals in each population (i.e., 30 - 200); the μGA uses a micro population of five individuals (Krishnakumar, 1989). A brief description of the steps in using GA for RO system optimization is as follows:

1- **Initial Population:** The GA randomly generates an initial population of coded strings representing RO system solutions of population size \(N\). Each of the \(N\) strings represents a possible pressure difference across the membrane, \(\Delta P\). The population sizing of the binary encoding; used in this study; is calculated as:

\[
\text{Population size} = \text{order} \left( \frac{I}{K} \times 2^k \right)
\]

where, \(I\) is the number of chromosomes and \(K\) is the average size of the schema of interest (effectively the average number of bits per parameter, i.e. approximately equal to (Number of chromosomes/Number of parameters), rounded to the nearest integer), Goldberg et al. (1992).

2- **Computation of Permeate Volumetric Flow Rate:** For each \(N\) string in the population, the GA decodes each substring into the corresponding pressure difference \(\Delta P\) and computes the permeate volumetric flow rate, \(Q_w\). The GA determines \(Q_w\) of each trial of pressure difference for the RO system in the current population.

3- **Modeling of Each RO System:** The modeling equations of the RO system computes \(C_p\) under the system specifications for each of the system designs (according to possible \(\Delta P\)) in the population. The value of \(C_p\) is compared with \(C_{p,d}\), Eq. (17), and any deficit in \(C_p\) is noted.

4- **Computation of Penalty:** The GA assigns a penalty if the RO system does not satisfy the desired permeate concentration constraint. The permeate concentration deficit is used as the basis for computation of the penalty. The permeate concentration deficit is multiplied by the penalty coefficient, Eq. (20).

5- **Computation of Objective Function:** The objective function, \(Z\) in the current population is taken as the sum of the permeate volumetric flow rate, \(Q_w\), which is to be maximized (Step 2) minus the penalty (Step 4), Eq. (21).

6- **Computation of the Fitness:** The fitness of the coded string, \(f\) is taken as some function of the objective function, \(Z\). As the objective function is to be
maximized, \( f = Z \), (Step 5), while for an objective function to be minimized, it can be computed as the inverse \((1/Z)\) or the negative value \((-Z)\). For the proposed RO system in the current population, \( f = Z \).

7- **Generation of a New Population using the Selection Operator:** The GA generates new members of the next generation by a selection scheme. In GARO program, the *tournament selection* is used.

8- **The Crossover Operator:** Crossover occurs with some specified probability of crossover for each pair of parent strings selected in Step 7. In GARO program, the *single-point crossover and uniform crossover* are used. The crossover probability for single-point crossover = 0.6 to 1.0, a value (0.6 or 0.7) is recommended. For uniform crossover, a value of 0.5 is recommended.

9- **The Mutation Operator:** Mutation occurs with some specified probability of mutation for each bit in the strings which have undergone crossover. In GARO program, the *creep mutation and jump mutation* are used. The jump mutation probability typically set = \((1/\text{Population size})\). The creep mutation probability typically set = \((\text{Number of chromosomes/Number of parameters}/\text{Population size})\). Note that mutations are not applied in the \(\mu\)GA since enough diversity is introduced after convergence of a \(\mu\)-population.

10- **Elitism:** Elitism is a method to copy the chromosomes (or few best chromosomes) to the new population. The rest of the population is constructed in ways described above. Elitism can rapidly increase the performance of GA, because it prevents a loss of the best-found solution, so it is used in GARO program.

11- **Production of Successive Generations:** The use of the three operators described above produces a new generation of RO systems using Steps 2 to 10. The GA repeats the process to generate successive generations. The last value of \(Q_w\) is stored and updated as bigger alternatives are generated.

Figure 1 illustrates the flow chart of main procedures of GA used in the present optimization program GARO.

The procedure of optimization in the present study depends on five main steps as shown in Fig. 2 as,

1- Perform the RO modeling to coefficients \(a\) and \(b\).
2- Apply GA technique to produce the optimal pressure difference \(\Delta P\).
3- Solve Eq. (4) numerically to obtain \(J_w\). \(C_p\) is evaluated using Eq. (5).
4- Compute the penalty and fitness.
5- Compare between produced \(\Delta P\) and generate the best solution.
Counting the number of chromosomes required for the specified input encoding

Loop from $I = \text{istart}$ to $\text{maxgen} + \text{istart} + 1$
Step = 1

Evaluates the population
Assigns fitness
Establishes the best individual
outputs information

Loop from $J = 1$ to $\text{npopsize}$
Step = $nchild$

Selection
Tournament selection

Crossover
Performs crossover

Mutation
Performs mutation (jump or creep)

Elitism
Check if the best parent was replicated

Micro – GA Technique

For microGA

No

Yes

Elitism
Check if the best parent was replicated

Restart
Writes restart information

Output information

End

Figure 1. Flow chart of main procedures of GA
Twelfth International Water Technology Conference, IWTC12 2008, Alexandria, Egypt

Figure 2. Flow chart of RO system optimization
CASE STUDY

An actual RO plant has been selected to apply the developed program for the optimization to evaluate the design of the RO plant, also, to test the capabilities of the developed model in a real and large plant.

Nuweiba RO Plant in Egypt has a capacity of 5000 m$^3$/day. It consists of the following main systems; the intake, the raw water pretreatment unit and cartridge filters, the RO membrane unit and the post treatment system as illustrated in Fig. 3. Saline water is pumped from the beach wells through the deep well pumps to a PVC header and then to the sand filters (activated carbon filters). During this process, the water is sterilized to prevent the growth of bacteria and algae. Post treatment of the product water consists of chlorinating to allow chlorine residual and pH adjustment within the acceptable range of 7.5 to 8.5 ppm. The plant is provided with one cartridge filter which ensure that particles larger than 5 microns, carried over from the dual media filters will not enter the membranes.

The plant specification, data and design parameters used in the modeling are given in Table 2. The membranes stainless steel skid consists of 15 vessels; each one contains 5 elements of membranes of spiral wound type. The membrane is only a skin of about 0.0025 mm thick. The membranes are rather porous plastic with active chemical sites. Its permeability is affected by water chemical contents, temperature, pressure and salinity. The pressure required to operate the RO plant in Nuweiba City is 60-70 bar.

![Figure 3. A schematic diagram of RO desalination plant in Nuweiba City](image-url)
Table 2 Nuweiba reverse osmosis plant specification

**Plant:**
- Number of Units: 5
- Capacity of Unit (m³/day): ≈ 1000

**Unit:**
- Product Water Flow (m³/h) (m³/day): 47 (1128)
- Reject Water Flow (m³/h) (m³/day): 103 (2472)
- Total Water Feed Flow (m³/h) (m³/day): 150 (5640)

**Operation condition:**
- Temperature (°C): 28
- Bulk Seawater Concentration (ppm): 44000
- Permeate Water Concentration (ppm): 350
- Membrane Pressure Difference, ΔP (bar): 65.845

**Membranes:**
- Membrane Type: TORAY SU 820
- Number of Vessels: 15
- Number of Membranes in Vessel: 5
- Total Number of Membranes: 75
- Diameter of Membrane (inch) (m): 8 (0.2032)
- Length of Membrane (inch) (m): 40 (1.016)
- Membrane Surface Area (ft²) (m²): 300 (27.87)
- Width of Membrane B (m): 27.432
- Spacer Thickness $d_{SP}$ (m): 0.00054
- Porosity $\varepsilon$: 0.91
- Hydraulic Diameter $d_h$ (m): 0.0007226
- Specific Surface of Spacer $a_{SP}$ (1/m): 14814.815

The permeability coefficients of water and salt $a$ and $b$; Eqs. (1) and (2); are obtained by GARO program using the operating data of Nuweiba RO plant. The values of $a$ and $b$ are $1.1212 \times 10^{-06}$ m/bar.s and $2.264 \times 10^{-07}$ m/s respectively. These values depend on the membrane and do not depend on the values of ΔP. Therefore, these values are used in the optimization process.

The values of the computational parameters of GA used for the optimization are given in Table 3.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Maximum number of generations</td>
<td>500</td>
</tr>
<tr>
<td>Random seed number</td>
<td>-1220</td>
</tr>
<tr>
<td>Probability of crossover</td>
<td>0.5</td>
</tr>
<tr>
<td>Probability of mutation</td>
<td>0.2</td>
</tr>
</tbody>
</table>
The computational time taken for optimizing the case study is 2 min. on a Pentium IV, 1.7 GHz, 256 MB Ram.

RESULTS AND DISCUSSION

The single-objective optimization of Nuweiba RO plant is the maximization of the permeate flow rate, $Q_w$, and the optimization is solved for finding the optimal value of feed water pressure difference, $\Delta P$ which fulfill the constraint that the resulted permeate concentration is less than a desired value.

Figures 4, 5 and 6 illustrate the numerical results of the GA optimization and the experimental results obtained from the Nuweiba RO plant, Djebedjian et al. (2007) and Gabr (2007). In these figures the operating point of the RO plant ($Q_w = 235 \text{ m}^3/\text{h}$, $\Delta P = 65.845 \text{ bar}$, and $C_p = 350 \text{ ppm}$) is also shown. It is worth to mention that in these calculations the RO plant is in operation with 5 units, while that given in the experimental study; Djebedjian et al. (2007) and Gabr (2007); only one RO unit was experimentally tested.

Figure 4 shows the optimal operating pressure difference $\Delta P$ corresponding to the permeate volumetric flow rate $Q_w$. The relationship is approximately linear. Therefore, the maximum value of $Q_w$ corresponds to the upper bound of $\Delta P$ (100 bar in this case). The modeling of the RO plant is seen to be in a good agreement with the experimental results obtained in the case study with a considerable difference at lower permeate flow rates.

On the other hand, the relationship between the permeate concentration $C_p$ and the permeate volumetric flow rate $Q_w$ is illustrated in Figure 5. The constraint that $C_p$ to be lower than the desired value $C_{p,d}$ is fulfilled. Under these conditions, $C_p$ decreases gradually below $C_{p,d}$ with the increase of $Q_w$ till it reaches the value of 189.3 ppm at $Q_w = 485.496 \text{ m}^3/\text{h}$. Similar to the previous figure, the trend of the modeling results is in a good with the experimental results and the deviation increases with decreasing the permeate flow rate as shown in the figure.

The values of $\Delta P$, $Q_w$ and $C_p$ in Figures 4 and 5 are used to show the relationship between $C_p$ and $\Delta P$ (Figure 6). Similar characteristics are found for that obtained in $C_p$ versus $Q_w$. An excellent agreement between the experimental and modeling results is observed in all points exceeding that with minimum pressure difference.
Figure 4. Optimal solutions – Relationships between pressure difference and permeate flow rate

Figure 5. Optimal solutions – Relationships between permeate concentration and permeate flow rate
From the above figures, it can be seen that the operating point of the RO plant is exactly on the optimal results obtained from the GARO Program. This is a good evidence for the perfection of this program and its ability to define the optimal operating point of a new designed RO desalination plant.

**CONCLUSIONS**

In this study, a methodology is developed for optimization of the RO desalination system performance. The solution-diffusion model is used for the modeling the system performance. The optimization process is achieved by the genetic algorithms technique. The objective of optimization is to find the best pressure difference across the RO membrane which maximizes permeate volumetric flow rate and fulfill the permeate concentration constraint (the permeate concentration to be less than the desired value).

A computer program is written in FORTRAN, GARO program (Genetic Algorithm Reverse Osmosis) to include the methodology. A binary-coded micro-genetic algorithm is linked with the equations describing the performance of RO systems. The methodology is tested on a real RO desalination plant in Nuweiba City, Egypt.

The application of the GARO program on the Nuweiba RO plant yields the following conclusions:

1) The relationship between the operating pressure difference across the RO membrane and permeate volumetric flow rate is approximately linear.
2) The permeate concentration decreases with the increase in volumetric flow rate and the membrane pressure difference.

3) The theoretical results from the optimization program are seen to be in a good agreement with that experimentally obtained specially at higher flow rates.

It is recommended in a future study to apply the genetic algorithms optimization technique to different designs of the RO desalination systems.

REFERENCES


