Operational optimization of SWRO process with the consideration of load fluctuation and electricity price

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Abstract: In this work, the operational optimization of seawater reverse osmosis (SWRO) process is studied to reduce the energy cost. Effects of load fluctuation and electricity price change were considered, and storage tanks were used to adjust the water production and balance the freshwater demand. Based on comprehensive first-principles, a detailed and accurate mathematical model with spiral-wound membranes, water storage tanks and water demands is developed and validated by plant data and the ROSA9.0 simulation package. The operational optimization problem with the form of DAEs was solved with simultaneous approach and IPOPT solver. Computing results of real SWRO plant were then investigated. It is shown that, compared with conventional operation and operation with constant water level, about 27.88% and 24.17% of energy cost, respectively, can be saved by optimizing both feed flowrate and feed pressure within normal range. Optimal profiles of key performance states were analyzed and future work for operational cost saving are described.

Keywords: Desalination; Seawater Reverse Osmosis; operational Optimization; DAE.

1. INTRODUCTION

The shortage of freshwater resources is expected to worsen with the growth of population and industrialization, as well as climate change. Desalination is one of the most feasible ways to obtain freshwater, especially in the coastal regions and islands. The two most widely used desalination techniques are reverse osmosis (RO) and multi-stage flash distillation (MSF), whose market shares are about 42.5% and 39.1% of worldwide installed capacity in the past decade. In recent years, RO has significantly increased its market share for seawater desalination, because of the significant progress in membrane technology and the advantages of this technology offers compared to the thermal desalination techniques. Among the membrane modules, spiral-wound type occupies the largest market share because of its relative ease of cleaning, fabrication technology and very large surface area per unit volume.

As we know, RO process is also an energy intensive process. In typical seawater RO system, the cost of energy can approach 45% of the total production cost due to the fact that the system operation requires very high feed pressure in order to achieve the desired permeates production rate. In the past decades, researchers have developed ways to reduce energy cost through many approaches, including improving the performance of membranes, building more accurate performance models, designing more economical flowsheet and optimizing the operation of the system. Since the 1950’s, the total processing cost is now reduced from more than 10 dollars to about half a dollar per cubic meter water.

Reducing the total cost of seawater desalination through system engineering approaches has attracted considerable attention. A number of researchers have previously considered optimization of design and operation of RO process. Zhu et al. optimized the operation of an RO network operating under several variable operating conditions. See et al. studied optimal configuration and optimal operations of RO plant, and particular attention was given to the decay in membrane permeability, the increase in the membrane fouling with the membrane life, and the optimal membrane cleaning schedule. Geraldes et al. analyzed the configuration and operating condition under different stages, in order to determine optimal module arrangement and capital cost. Palacin et al. studied the operation of RO plant under optimal energy consumption and then proposed a hybrid predictive control method. Li et al. studied optimal plant operation of brackish water reverse osmosis (BWRO) desalination to reduce specific energy consumption. Based on the solution of optimal problem formulated by first principle model, about 16% cost reduction can be achieved. Ghobeity optimized the operation of SWRO with consideration of these time-varying factors to reduce electricity charges.

In this work, we investigate energy cost saving through systematic optimization of an SWRO process. Based on the detailed process model formulated by DAEs, the operational optimization problem is formulated and then solved by IPOPT under the platform of GAMS. Much more energy cost saving is expected to be achieved by the proposed method through case study.

2. DESCRIPTION OF SWRO FLOWSHEET

The general flowsheet of SWRO which includes 4 sections can be found in the specialized literature (as shown in Fig.1). Generally, salty feed water is firstly pre-treated to avoid membrane fouling, and then sent through the membrane modules (permeates) by high-pressure pumps. Under high pressure, pure water permeates through the membranes and the salty water becomes highly concentrated brine. The obtained permeate water flows directly into a storage tank, where pH is adjusted and other post-disposal...
treatments are carried to satisfy residential water quality requirements. The brine at high pressure is sent to an energy recovery device before discharge. To achieve a high recovery in a single stage, several spiral-wound modules were held in series in one cylindrical pressure vessel.

For the real case, fluctuation of freshwater demand is inevitable. Fig2 shows typical freshwater daily demands, from which the quasi-periodic law can be obtained. Since the energy cost is largely affected by the electricity price, and the electricity price is different at different hours (Fig.3), minimizing the energy cost will lead to different optimal feed operation over time. From the flowsheet of SWRO system, it is reasonable to adjust the water level of the storage tank to reduce the water production cost and to satisfy the water demand meanwhile. So with the consideration of electricity price and fluctuation of freshwater demand, optimizing the daily operation will obtain more benefits through reducing the energy cost. To realize the above aim, the prediction of freshwater demand and process model should be obtained in advance.

![Diagram of SWRO process](image)

**Fig1. Basic schematic diagram of a SWRO process**

![Typical demand of produced freshwater](image)

**Fig2 Typical demand of produced freshwater**

![Change of electricity price along hours](image)

**Fig3 Change of electricity price along hours**

### 3. MODELING OF SWRO PROCESS WITH DEMAND FLUCTUATION

#### 3.1 Modelling of spiral wound RO process

Based on solution–diffusion model and film theory, a simpler model of RO process determined to optimize the operation of RO plant. Senthilmurugan et al. and Oh et al. have applied the solution-diffusion model modified with the concentration polarization model for analyzing the operation and performance of RO process, but for simplicity, the pressure drop and velocity of seawater in pressure vessel was approximated by average method. For the RO process, the overall fluid and solute mass balance equations are:

$$ Q_p = Q_f - Q_r $$  \hspace{1cm} (1)
$$ Q_f C_f = Q_r C_r + Q_p C_p $$  \hspace{1cm} (2)
$$ Q_p = n_l W \int_0^L J_v dz $$  \hspace{1cm} (3)

Here subscripts f, r, and p refer to the feed, reject (brine) and permeate (product) streams. Q and C refer to the flowrate and salt concentration respectively. The local water and salt flux may be calculated from the Kimura–Sourirajan solution–diffusion mass transport relations. $n_l, W$ and $L$ refer to leaf number, width and length of RO module, respectively. The solution–diffusion model is assumed to be valid for the transport of solvent and solute through the membrane; the solvent flux $J_v$ and solute flux $J_s$ through membrane are expressed by the following equations:

$$ J_v = A_w (P_r - P_d - P_\Delta - \Delta \pi) $$  \hspace{1cm} (4)
$$ J_s = B_s (C_m - C_{sp}) $$  \hspace{1cm} (5)
$$ P_b = P_f - P_d $$  \hspace{1cm} (6)
$$ \Delta P = (P_b - P_p) $$  \hspace{1cm} (7)
$$ J_v = A_w (\Delta \pi - \Delta \pi) $$  \hspace{1cm} (8)

where $A_w$ is the solvent transport parameter, $P_f$ is the feed pressure, $P_b$ and $P_d$ are the pressure and pressure drop along the channel of spiral-wound membrane. $P_r$ is the pressure of permeate side, which is generally assumed as environmental pressure. $\Delta \pi$ is the pressure loss of osmosis pressure. $B_s$ is the solute transport parameter, $C_w$ and $C_p$ are solute concentration at the membrane surface on the feed side and solute concentration on the permeate side respectively. $C_{sp}$ is the value of $C_{sp}$ at the end of module, i.e., $C_{sp} = C_{sp}(L)$. $A_w$ and $B_s$ are expressed as:

$$ A_w = A_{w0} \exp(\alpha_s T - \frac{273}{273} - \frac{\alpha_s (P_f - P_d)}{2}) $$  \hspace{1cm} (9)
$$ B_s = B_{s0} \exp(\beta_s T - \frac{273}{273}) $$  \hspace{1cm} (10)

Where $A_{w0}$ and $B_{s0}$ are intrinsic transport parameter in standard condition, $\alpha_s, \alpha_t$ and $\beta_s$ are constant parameters for transport in T represents operational temperature in degrees Kelvin. The osmotic pressure is nearly linearly related to concentration by:

$$ \Delta \pi = RT (C_m - C_p) $$  \hspace{1cm} (11)

here $R$ is the gas law constant.

Solution of the above equations requires knowledge of the plant specifications and parameters as well as the solute concentration $C_{sp}$ at the membrane wall, which is quite
different from the bulk concentration $C_b$ due to the CP (concentration polarization) phenomenon. According to steady-state material balance around the boundary layer and CP theory, the following simple expression is developed:

$$\phi = \frac{C_u - C_p}{C_b - C_p} = \exp\left(\frac{J_v}{k_c}\right)$$  \hspace{1cm} (12)

The bulk concentration $C_b$ and solvent flux $J_v$ vary along the membrane channel, the computation of the mass transfer coefficient $k_c$ is given by:

$$Sh = \frac{k_c d_s}{D_{AB}} = 0.065 Re^{0.875} Sc^{0.25}$$  \hspace{1cm} (13)

$$Re = \frac{\rho V d_s}{\mu}$$  \hspace{1cm} (14)

$$Sc = \frac{\mu}{(\rho D_{AB})}$$  \hspace{1cm} (15)

where $\rho$ is the density of permeate water, $d_s$ is hydraulic diameter of the feed spacer channel, $\mu$ is kinematic viscosity and $D_{AB}$ is dynamic viscosity.

The relationship between $J_v$ and $J_s$ is

$$J_s = J_v \cdot C_p$$  \hspace{1cm} (16)

The pressure loss along the RO membrane is:

$$\frac{dP_b}{dz} = -\lambda \frac{\rho V^2}{d_e^2}$$  \hspace{1cm} (17)

Where

$$\lambda = 6.23 K_r Re^{-0.3}$$  \hspace{1cm} (18)

$K_r$ is the empirical parameter. Since the pressure along the RO membrane $P_b = P_f - P_d$, so

$$\frac{dP_b}{dz} = -\frac{dP_d}{dz} = \frac{\lambda \rho V^2}{d_e^2}$$  \hspace{1cm} (19)

at $z=0$, $P_b = P_f$, at $z=L$, $P_b = P_d$.

Here $V$ is the axial velocity in feed channel, which satisfies

$$\frac{dV}{dz} = \frac{2J_v}{h_{sp}}$$  \hspace{1cm} (20)

at $z=0$, $V = V_f = \frac{Q_f}{n_e W_{h_{sp}}}$  \hspace{1cm} (21)

at $z=L$, $V = V_r = \frac{Q_r}{n_e W_{h_{sp}}}$  \hspace{1cm} (22)

$h_{sp}$ is height of the feed spacer channel.

The bulk concentration $C_b$ varies along the membrane channel, and can be given as:

$$\frac{dC_b}{dz} = \frac{2J_v}{h_{sp}V}(C_b - C_p)$$  \hspace{1cm} (23)

and at $z=0$, $C_b = C_f$, at $z=L$, $C_b = C_r$.

From the above equations, $Q_p$ and $C_p$ at given operational conditions and specification of membrane can be obtained, and we can get the water recovery rate and specific energy consumption $SEC$ by the following equations:

$$Rec = \frac{Q_p}{Q_f}$$  \hspace{1cm} (24)

$$SEC = \frac{P_f Q_f}{\varepsilon_p - \varepsilon_{ef}}$$  \hspace{1cm} (25)

Salt rejection coefficient is also an important parameter reflecting the performance of the RO process, and it is denoted as:

$$R_y = \frac{(C_f - C_p)}{C_f} \times 100\%$$  \hspace{1cm} (26)

Here $\varepsilon_p$ and $\varepsilon_{ef}$ represent the mechanical efficiency and energy recovery efficiency, respectively.

3.2 Dynamic model of storage tank

Assuming that the total produced freshwater is equal to freshwater supply, the dynamic equations can be deduced as follows:

$$\frac{dH_t}{dt} = \frac{(Q_p - Q_{out})}{S_t}$$  \hspace{1cm} (27)

$$\frac{dC_{i, out}}{dt} = \frac{1}{S_t H_t} (Q_p C_p - Q_{out} C_{i, out} - C_{i, out} S_t \frac{dH_t}{dt})$$  \hspace{1cm} (28)

$S_t$ and $H_t$ represent the area and the height of the storage tank, The height level must satisfy $H_{lo} < H_t < H_{up}$, here $H_{lo}$ and $H_{up}$ is the height level constraints to keep safety. $Q_p$ represents the flowrate of permeate water, $Q_{out}$ represents the output flowrate of freshwater for demand. $C_p$ and $C_{i, out}$ represent concentration of permeate water and output freshwater respectively.

3.3 Freshwater schedule based on demand prediction

To satisfy the requirement of freshwater demand, SWRO plants schedule their production in advance based on the history data. Since the freshwater demand is quasi-periodic, it can be predicted by methods such as nonlinear least squares or regression. Generally, auto-regression leads to good prediction results for this problem. The equation is formulated as follow:

$$F_{k,\theta+1} = \omega_1 x_{k, \theta} + \omega_2 x_{k, \theta+1} + \cdots + \omega_n x_{k, \theta-n+1} + \omega_0$$  \hspace{1cm} (29)

where $n$ represents the number of previous days; $k$ represents different hour; $x_{k, \theta}$ is observed data (flowrate) of $\theta$th day at $k$th hour; $\omega_0, \omega_1, \ldots, \omega_n$ are parameters obtained by auto-regression; and $F_{k,\theta+1}$ is the predicted value of the $(\theta+1)$th day at the $k$th hour.

4. OPERATIONAL OPTIMIZATION FORMULATION

With the consideration of periodic outflow fluctuation and change of electricity price, we now minimize the energy cost over 24 hours, and also satisfy constraints on equipment bounds, water quality and load demands. The minimum energy cost problem (Opt1) is given by:

$$\min \int_{t_0}^{t_f} Price(t) \times (SEC \times Q_p) dt$$  \hspace{1cm} (30)

s.t. Eqns.(1)-(28)  \hspace{1cm} (31)

$$H_i(0) = H_i(t_f)$$  \hspace{1cm} (32)
Initial conditions:
\[
H_y(0) = H_y^0 \quad (33)
\]
\[
C_{t,\text{out}}(0) = C_{t,\text{out}}^0 \quad (34)
\]

Bounds:
\[
P_{f,\text{m}} \leq P_f \leq P_{f,\text{up}}, \quad Q_{f,\text{m}} \leq Q_f \leq Q_{f,\text{up}}
\]
\[
C_{p,\text{m}} \leq C_p \leq C_{p,\text{up}}, \quad T_{\text{lo}} \leq T \leq T_{\text{up}}
\]
\[
\phi \leq \phi_{\text{max}}, \quad \text{Rec}_{\text{lo}} \leq \text{Rec} \leq \text{Rec}_{\text{up}}
\]
\[
S P_{f,\text{m}} \leq S p \leq S P_{f,\text{up}}, \quad H_{\text{min}} \leq H_y \leq H_{\text{max}} \quad (35)
\]

Here \( t_f \) is set as 24 hours. And the height level of storage tank at initial time is equal to that of time \( t_f \) \((\text{Eqn}(32))\) to ensure the same conditions over the next period. \( \text{Price}(t) \) is the price of electricity over time, \( \text{SEC} \) is the specific energy consumption, which is directly related with the RO process and is affected by the manipulated variables of feed flowrate and feed pressure. In this work, the manipulated variables are adjusted each hour with the assumption that the RO process is at pseudo steady-state; we assume the transition regime from one steady state to another is relatively short\(^{29-30}\). Because the change of height and concentration of output is a slow dynamic process, the optimal problem can be considered as a multi-period process. The objective function can be reformulated as:

\[
\min \sum_{i=1}^{24} \text{Price}(i) \times (\text{SEC}(i) \times Q_f(i)) \quad (36)
\]

Currently, DAEs optimization problems are solved by various strategies that apply nonlinear programming (NLP) solvers to the DAE models\(^{31-33}\) such as (1)-(28). To solve Opt1, we applied a simultaneous method to convert the DAEs into NLP by approximating state and control profiles by a family of polynomials on finite elements. These polynomials can be represented as power series, orthogonal polynomials or in Lagrange form. Here, we use the following monomial basis representation for the differential profile, which is popular for Runge-Kutta discretizations\(^{34}\). The differential variables are required to be continuous throughout the time (or space) horizon, while the control and algebraic variables are allowed to have discontinuities at the boundaries of the elements\(^33\). The collocation method converts the dynamic optimization problem into a large-scale NLP, which is denoted as Opt2 here. IPOPT was used for the solution.

5. CASE STUDY AND RESULTS

A SWRO plant was considered for case study. The main process of the plant is the same as Fig.1. Commercial spiral-wound RO membrane of SW30HR-380 with 6-9 modules were selected in series in each pressure vessel, and 55 pressure vessels were grouped to comprise the freshwater production unit. Storage tank was used to store the permeate water and then satisfy the output demand. Feed condition and storage tank structure are listed in Tables 1.

5.1 Model validation

The key performance parameters such as water recovery ratio and salt reject were computed by the above equations, and then were compared with field data and those from ROSA9.0. As can be seen from Table 2, the overall results obtained from the established model are in good agreement with those obtained from both ROSA and the field data. Though the real water recovery ratio and salt reject are lower than our model and that of ROSA9.0, the relative error is quite small.

Table 1. Feed condition and tank information

| Feed condition | Value |
|----------------|-------|
| C(f/kg/m³)     | 30    |
| T(K)           | 298   |

Table 2. Comparison results of water recovery and salt reject

| Item          | WR(%) | SR(%) |
|---------------|-------|-------|
| field data    | 41.6  | 99.37 |
| ROSA9.0       | 42.7  | 99.58 |
| Model         | 42.1  | 99.52 |

Simulation of our model at different feed pressure yields the profile of SEC shown in Fig.4, and from the profile it can be seen that significant energy saving can be obtained through optimizing the operational variables.

Fig.4 SEC value change curve along the feed pressure

Based on eqn.(29), the freshwater output demand is predicted. Table 3 shows the relative errors and accumulated errors between real data and predicted data. Since the accumulated error is quite low, it is good enough to be used for the operational optimization.

Table 3. Prediction value and error of outflow

| Time (hour) | Real data (m³/h) | Predicted data (m³/h) | Relative error (%) | Accumulative error (m³/h) |
|-------------|------------------|-----------------------|--------------------|--------------------------|
| 1           | 275              | 279                   | 1.39               | 4                        |
| 2           | 246              | 262                   | 6.64               | 20                       |
| 3           | 236              | 249                   | 5.23               | 32                       |
| 4           | 245              | 239                   | -2.28              | 27                       |
| 5           | 236              | 238                   | 0.65               | 28                       |
5.2 Operational optimization of SWRO process with load fluctuation and different electricity price

Generally, the real seawater desalination plant was operated under steady conditions; the storage tank water level is frequently kept constant for convenience; and feed flowrate is always the first selection to satisfy the requirement of output demand for freshwater. Minimizing the SEC is an effective way to save energy, but is not necessarily the most cost saving way.

Based on the established SWRO process model, larger cost saving may be achieved by optimizing the operational problem which is formulated by equations (30)-(35). Three Radau collocation points and 100 spatial finite elements were used to discretize the complex problem along feed channel; 24 temporal elements with 3 collocation points were used to discretize the 24 hours. The discretized problem (here denoted as Opt2) has more than 100,000 variables and constraints. The information about the membrane module, storage tank and feed condition are the same as in Table 1. Predicted value of freshwater demand is shown in Table 3. To demonstrate the cost saving of the proposed problem, the results were compared with the general optimal case and the conventional one named Case1 and Case2 in this paper:

Case1: the water level is kept constant; permeate water is equal to output water; the feed flowrate and feed pressure are optimized to save total energy cost.
Case2: the water level and SWRO feed flowrate are kept constant; feed pressures $P_f$ are adjusted to satisfy the output demand of freshwater.

Under different cases, IPOPT can find the optimal solution in 400-750 CPU seconds. Solution of the optimization problem yields an optimal energy cost of 8117.26 CNY per day as well as the profiles of manipulated variables and state variables. The profiles were compared with the results from the solution of Case1 and Case2, which can be seen from Fig.5 to Fig.11.

In Case 2 the water level was fixed at 4 meters and the feed flowrate was fixed at 1000 m$^3$/h. The manipulated variables were obtained as well as the objective function by the same solver, which lead to the optimal energy total cost of 11254.49 CNY per day.

Next, for Case1, the feed water level was fixed at 4 meters, but flowrate was allowed to vary. Here the solution of the optimization problem yields an optimal energy cost of 10703.92 CNY per day. Compared with the conventional operation of Case2, Case1 can decrease 550.57 CNY energy cost per day, which is about 4.89% of total energy cost in Case2. Finally if we allow both the flowrate and water level to vary, the proposed method can save 3137.2 CNY per day, which is about 27.88% energy saving compared with Case2. Compared with Case1, the proposed method can achieve cost saving of 2586.7 CNY per day. This means: compared with Case2 and Case1, more than one million CNY and 0.87 million CNY can be saved (assuming annual operation has 320 days).

| Case  | Objective (CNY/d) | Cost Saving Value (CNY/d) | Cost Saving Ratio (%) |
|-------|------------------|--------------------------|-----------------------|
| Case2 | 11254.49         | 0.00                     | 0.00                  |
| Case1 | 10703.92         | 550.57                   | 4.89                  |
| opt2  | 8117.26          | 3137.23                  | 27.88                 |

Fig.5 shows the profile of feed flowrate over 24 hours with different operating schemes. Under Case2 the feed flowrate is kept constant. Under Case1 feed flowrate is relatively small for the aim of energy saving, and it increases when the load production is lower than output during those hours. And it falls at about 22-24 hours, which means that the water production is lower than output during these hours, in order to reduce the effect of high electricity price.

Detailed profiles for water recovery and salt rejection can be seen from Fig.9 to Fig.10. Fig.10 shows the profiles of water recovery under different cases. Our optimal water recovery is higher than that of conventional Case2, it is helpful to cost saving. Compared with Case1, our optimal water recovery changes more frequently, and has the opposite trend as electricity price, which means that relatively high water recovery with low electricity can achieve more cost saving.
In this work, an accurate model including the RO process, water storage and water production prediction was established, and then the optimal operational problem to minimize the energy cost per day was formulated and discretized by simultaneous method. The large scale solver of IPOPT under GAMS was used for the solution. Then after model verification, the operational optimization was studied under different cases. Compared with the results of conventional operation, the optimization of Case2 and Case1 have the potential energy cost saving of about 27.88% and 24.17%, respectively. From profiles of feed flowrate and feed pressure, it can be seen that optimal results change more frequently and have the opposite trend as the electricity price. More detailed research including more accurate prediction of output freshwater flowrate, detailed consideration of membrane fouling and optimal control will contribute further benefits to the SWRO process. These topics will be considered in our future work.

6. CONCLUSIONS

ACKNOWLEDGEMENTS

This work was supported by National Key Technology Research and Development Program of the Ministry of Science and Technology of China (2009BAB47B06), the grants of National Natural Science foundation of China(No. 60904058; 61374142).

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