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[1-3]. 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[4]. 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[5]. 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[6-7].

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[8-10]. 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[11-16]. 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 [17].

Reducing the total cost of seawater desalination through system engineering approaches has attracted considerable attention[18]. A number of researchers have previously considered optimization of design and operation of RO process, Zhu[16] et al. optimized the operation of an RO network operating under several variable operating conditions. See[19] et al. studied optimal configuration and optimal operations of RO process, 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[20] analyzed the configuration and operating condition under different stages, in order to determine optimal module arrangement and capital cost. Palacin[21] et al. studied the operation of RO plant under optimal energy consumption and then proposed a hybrid predictive control method. Li[22] 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 [23].

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 GAMS24. 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[24-25] (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.

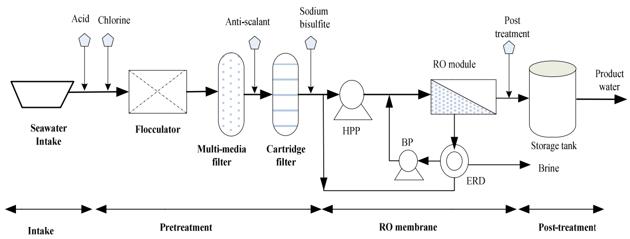

Fig1. Basic schematic diagram of a SWRO process

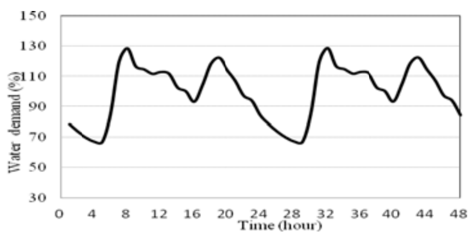

Fig.2 Typical demand of produced freshwater

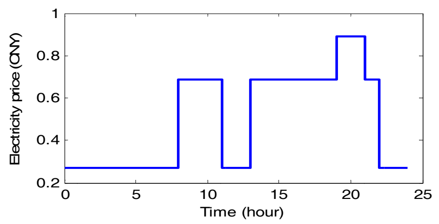

Fig.3 Change of electricity price along hours

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[26] et al. and Oh[27] et al. have applied the solution-diffusion model modified with the concentration polarization theory 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:

$$Q_p = Q_f - Q_r \tag{1}$$

$$Q_f C_f = Q_r C_r + Q_p C_p \tag{2}$$

$$Q_p = n_l W \int_0^L Jv dz \tag{3}$$

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[28] is assumed to be valid for the transport of solvent and solute through the membrane; the solvent flux *Jv* and solute flux *Js* through membrane are expressed by the following equations

$$Jv = A_w (P_f - P_d - P_p - \Delta\pi) \tag{4}$$

$$Js = B_s (C_m - C_{sp}) \tag{5}$$

$$P_b = P_f - P_d \tag{6}$$

$$\Delta P = (P_b - P_p) \tag{7}$$

$$Jv = A_w (\Delta P - \Delta\pi) \tag{8}$$

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_p 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_m and C_{sp} are solute concentration at the membrane surface on the feed side and solute concentration on the permeate side respectively. C_p is the value of C_{sp} at the end of module，i.e., C_p=$C_{sp}(L)$. A_w and B_s are expressed as:

$$A_w = A_{w0} \exp(\alpha_1 \frac{T-273}{273} - \alpha_2 (P_f - P_d)) \tag{9}$$

$$B_s = B_{s0} \exp(\beta_1 \frac{T-273}{273}) \tag{10}$$

Where A_{w0} and B_{s0} are intrinsic transport parameter in standard condition, α_1, α_2 and β_1 are constant parameters for transport in *T* represents operational temperature in degrees Kelvin. The osmotic pressure is nearly linearly related to concentration by:

$$\Delta\pi = RT(C_m - C_p), \tag{11}$$

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_m 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:

$$\phi = \frac{C_m - C_p}{C_b - C_p} = \exp(\frac{Jv}{k_c}) \quad (12)$$

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

$$Sh = \frac{k_c d_e}{D_{AB}} = 0.065 Re^{0.875} Sc^{0.25}, \quad (13)$$

$$Re = \rho V d_e / \mu \quad (14)$$

$$Sc = \mu / (\rho D_{AB}). \quad (15)$$

where ρ is the density of permeate water, d_e is hydraulic diameter of the feed spacer channel, μ is kinematic viscosity and D_{AB} is dynamic viscosity.

The relationship between Jv and Js is

$$Js = Jv * C_p \quad (16)$$

The pressure loss along the RO membrane is:

$$\frac{dP_d}{dz} = -\lambda \frac{\rho}{d_e} \frac{V^2}{2}, \quad (17)$$

Where $\lambda = 6.23 K_\lambda \mathrm{Re}^{-0.3}$, (18)

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

$$\frac{dP_b}{dz} = -\frac{dP_d}{dz} = \lambda \frac{\rho}{de} \frac{V^2}{2} \quad (19)$$

at z=0 , $P_b = P_f$, at z=L, $P_b = P_r$

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

$$\frac{dV}{dz} = -\frac{2Jv}{h_{sp}}, \quad (20)$$

$$\text{at } z=0,\ V = V_f = \frac{Q_f}{n_e W h_{sp}} \quad (21)$$

$$\text{at } z=L,\ V = V_r = \frac{Q_r}{n_e W h_{sp}} \quad (22)$$

h_{sp} is height of the feed spacer channel.
The bulk concentration C_b varies along the membrane channel, and can be given as:

$$\frac{\mathrm{d}C_b}{\mathrm{d}z} = \frac{2Jv}{h_{sp} V}(C_b - C_p), \quad (23)$$

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:

$$Rec = Q_p / Q_f \quad (24)$$

$$SEC = \frac{P_f Q_f / \varepsilon_p - P_r Q_r \varepsilon_{ef}}{Q_p}. \quad (25)$$

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

$$Ry = (C_f - C_p) / C_f \times 100\% \quad (26)$$

Here ε_p and ε_{pf} 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:

$$\frac{\mathrm{d}H_t}{\mathrm{d}t} = (Q_p - Q_{out}) / S_t \quad (27)$$

$$\frac{\mathrm{d}C_{t,out}}{\mathrm{d}t} = \frac{1}{S_t H_t}(Q_p C_p - Q_{out} C_{t,out} - C_{t,out} S_t \frac{\mathrm{d}H_t}{\mathrm{d}t}) \quad (28)$$

S_t and H_t represent the area and the height of the storage tank, The height level must satisfy $H_{t,lo}<H_t<H_{t,up}$, here $H_{t,lo}$ and $H_{t,up}$ 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 $C_{t,out}$ 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:

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

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

$$\min \int_0^{t_f} \mathrm{Price}(t) \times (SEC \times Q_p) \mathrm{d}t \quad (30)$$

$$\text{s.t.} \quad \text{Eqns.(1)-(28)} \quad (31)$$

$$H_t(0) = H_t(t_f) \quad (32)$$

Initial conditions:

$$H_t(0) = H_t^{\ 0} \tag{33}$$

$$C_{t,out}(0) = C_{t,out}^{\ 0} \tag{34}$$

Bounds:

$$P_{flo} \le P_f \le P_{fup}, Q_{flo} \le Q_f \le Q_{fup}$$

$$C_{plo} \le C_p \le C_{pup}, T_{lo} \le T \le T_{up}$$

$$\phi \le \phi_{\max}, Rec_{lo} \le Rec \le Rec_{up}$$

$$Sp_{lo} \le Sp \le Sp_{up}, H_{t\min} \le H_t \le H_{t\max} \tag{35}$$

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(Eqn(32)) to ensure the same conditions over the next period. *Price*(t) is the price of electricity over time, *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:

$$\min_{P_f(i),Q_f(i)} \sum_{i=1}^{24} \text{Price}(i) \times (SEC(i) \times Q_p(i)) \tag{36}$$

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
Cf(kg/m^3)	30
T(K)	298
Tank information	
Area of liquid level St (m2)	150
Max height limited (m)	15
Min height limited (m)	2
Initial concentration (kg/m3)	0.330
Initial water liquid level (m)	4

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.

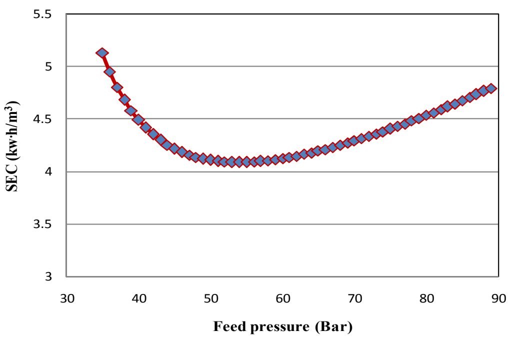

Fig.4 SEC value change curve along the feed pressure

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 (m^3/h)	Predicted data(m^3/h)	Relative error (%)	Accumulative error (m^3/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

6	296	303	2.39	36
7	412	425	3.04	48
8	432	457	5.70	73
9	407	414	1.79	80
10	386	407	5.36	101
11	396	397	0.20	102
12	383	401	4.60	119
13	385	397	2.93	130
14	390	364	-6.43	105
15	383	356	-7.20	78
16	354	331	-6.42	55
17	399	371	-7.01	27
18	439	421	-4.16	9
19	438	435	-0.75	5
20	418	406	-2.78	-6
21	397	380	-4.14	-23
22	347	346	-0.25	-23
23	318	333	4.80	-8
24	282	299	5.97	9
Total	8500	8509	0.10	9

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 found 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 m3/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 2586.7CNY 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).

Table 4. Optimal results under different cases

	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 output freshwater is high. Under the scheme of Opt2, we find that the feed flowrate is relatively high when electricity price is low, and is much lower when the electricity price is high; this explicitly explains how the significant cost saving is realized. The permeate flowrate has a similar trend over time as feed flowrate, which can be deduced from Fig.6. To obtain more permeate water at low electricity price, under the scheme of Opt2, the feed pressure is adjusted to about 70 bar, but at the high electricity price, it is decreased to less than 50 bar. Fig.7 gives the profile and the comparison of different schemes. From Fig.8, it also can be seen that: compared with the constant value of water level for Case1 and Case2, the water level changes significantly over time under the scheme of Opt2. It hits the peak at about 9-10 hour, which means that the production is greater 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.

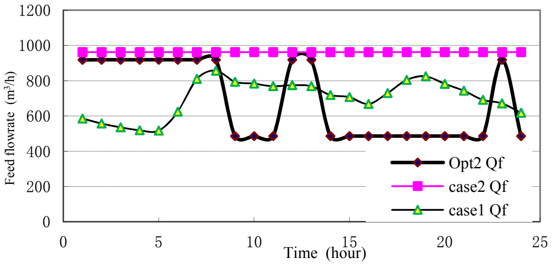

Fig.5 Feed flowrate profiles with different cases

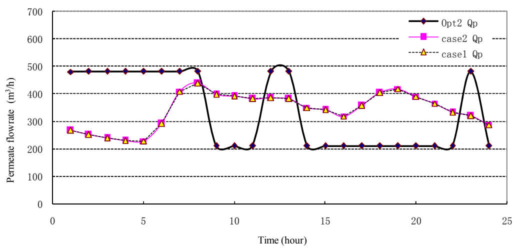

Fig.6 Permeate flowrate profiles with different cases

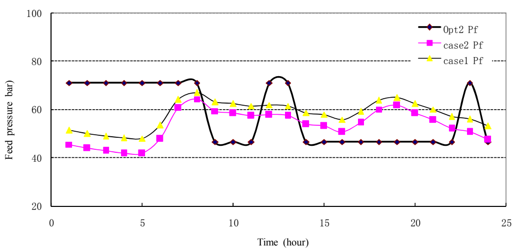

Fig.7 Feed pressure profiles with different cases

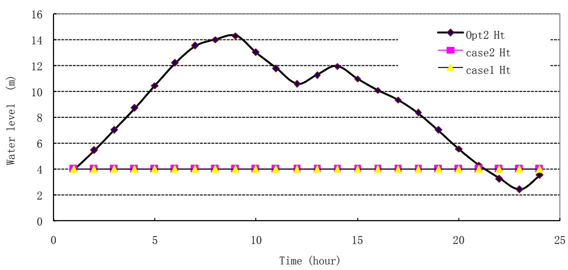

Fig.8 Water level profiles with different cases

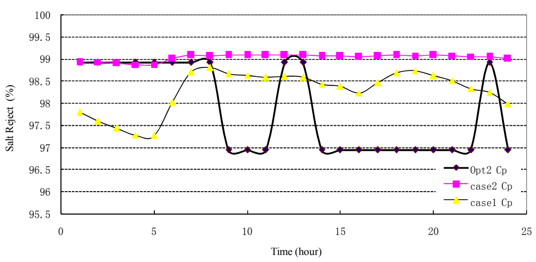

Fig.9 Salt reject curve with different cases

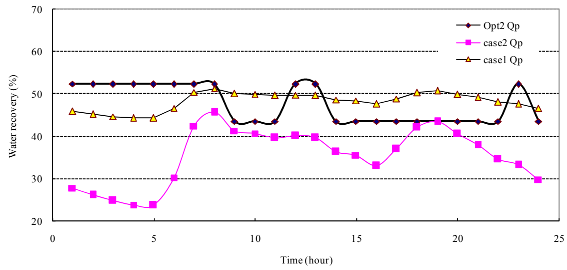

Fig.10 Water recovery curve with different cases

6. CONCLUSIONS

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.

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