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Meeting the Fixed Water Demand of MSF Desalination using Scheduling in gPROMS

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Multi-Stage Flash (MSF) desalination process has been used for decades for making fresh water from seawater and is the largest sector in desalination industries. In this work, dynamic optimisation of MSF desalination is carried out using powerful and robust dynamic simulation and optimisation software called gPROMS model builder. For a fixed freshwater demand, a number of optimal combinations of the factors such as heat transfer area, brine flow rate, cooling water flow rate, steam flow in brine heater, Top Brine Temperature, the number of stages, etc. are determined with the objective of maximising the performance ratio of the process (defined as the amount of fresh water produced per unit of energy input) considering the seasonal variations. An attempt has been made to develop an operational schedule for a particular day using dynamic optimisation.

1. Introduction

Global thirst will turn millions into water refugees. Increasing in population and standards of living together with water pollution are diminishing the quantity of naturally available fresh water while the demand for it is increasing continuously. While fresh water is an absolute necessity for sustainable development, more than 90 % of the world's surface water is saline. Multi Stage Flash (MSF) desalination process (Figure 1) has been used for decades for making fresh water from seawater (El-Dessouky and Ettouney, 2002).
The MSF plant behaviour changes with time due to corrosion and scaling (Said et al., 2011). Therefore, use of one optimal set point operation decided at the time of commissioning the new plant will not guarantee the expected profitability while meeting the operational constraints. Dynamic model provides a better insight into the process dynamics without conducting the lengthy and expensive tests on real plant. A typical MSF dynamic process model includes mass and energy balances, the geometry of the stages and thermo-physical properties (Mazzotti et al. 2000). Al-Fulaij et al. (2011) studied the stability of MSF desalination process using a dynamic model. Alsadaie and Mujtaba (2014) studied the effect of venting system design of Once-Through MSF process using a dynamic model. Tayyebi and Alishiri (2014) studied MSF control using a dynamic model. However, none of these studies reflected on the effect of dynamic seawater temperature changes on the performance of MSF processes. In this work, we develop an operational schedule of a Brine-Recirculation MSF process for a particular day using dynamic modelling and optimisation. Models for flash chambers, brine heater, mixer, splitter and orifice are developed individually and connected according to the physical existence shown in Tanvir and Mujtaba (2008). A framework is developed to optimize steam temperature profile of the MSF process for maximizing the performance ratio. The daily time horizon is split into several zones. The dynamic seawater temperature profile is considered to be piecewise constant in each time zone.

2. MSF model development

gPROMS allows user to model the transient behaviour of individual unit operations to be described in terms of mixed systems of integral, partial differential and algebraic equations (gPROMS, 2005). Like most

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of the modern simulator package gPROMS also provides an interface to develop a complex system from several subsystems. The Sub model (i.e., equipment model) can be connected graphically in *Master* model (i.e., flowsheet, recovery stage (Figure 2)). The model equations for one recovery stage, one rejection stage, splitter, mixer, brine heater, etc. are written as unit models respectively. Note the number of rejection stage is fixed to three in this work. With reference to Figure 1, some of the main model equations are given in the following. Further details on the model equations can be found in Sowgath (2007) and in Tanvir and Mujtaba (2008). The total number of stages are NS = NR+NJ (where, NR = number of stages in the recovery section, NJ = number of stages in the rejection section). From the degrees of freedom analysis, the total number of free variables is: 7NS + 11 and the differential state variables are 2NS+1. In optimization, a set of these variables are relaxed and optimized. The initial conditions are equal to the number of dynamic variables. This means 7NS+11 variables and the initial conditions must be specified before the model equations could be solved. The initial conditions (at time t = 0) of all the differential variables (such as $M_j^B, M_j^D, M_j^W, h_j^B, h_j^D, h_j^F, h_{BH}$) has to be given. Each model of different equipment can be presented as graphical form and connected graphically in process flowsheet (Figure 2).

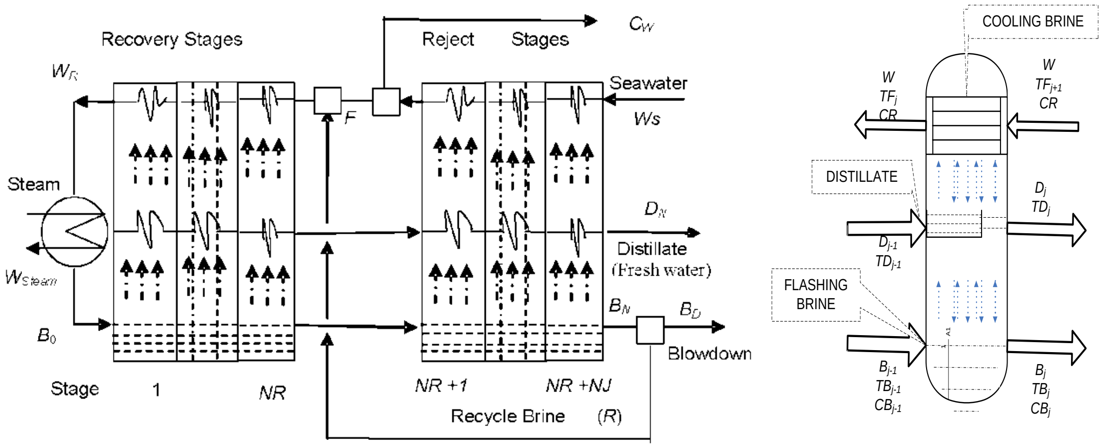

Figure 1: A typical MSF Process and its stage j

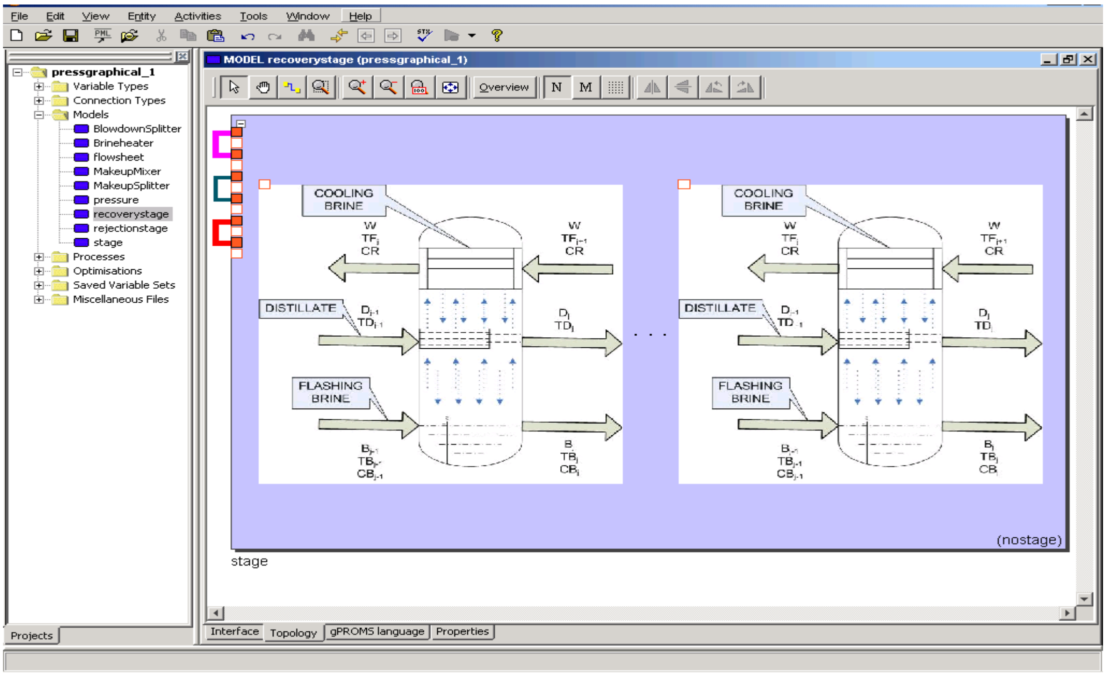

Figure 2: Internal Connection of Stages in Recovery Section in gPROMS

2.1 Stage Model

Total Mass Balance for the flashing brine: $\frac{dM_j^B}{dt} = B_{j-1} + B_j - V_j$ (1)

Salt Mass for the flashing brine: $\frac{d}{dt}\left(M_j^B \times X_j^B\right) = B_{j-1} \times CB_{j-1} - B_j \times CB_j$ (2)

Enthalpy balance for the flashing brine: $M_j^B \times h_j^B = B_{j-1} \times \left(h_{j-1}^B - h_j^B\right) - V_j \times \left(h_j^V - h_j^B\right)$ (3)

Mass balance for the distillate tray: $\frac{d}{dt} M_j^D = D_{j-1} + D_j - V_j$ (4)

Total Mass Balance for the Cooling Brine Tube: $W_j = W_{j+1} = W_T$ (5)

Salt Mass for the Cooling Brine Tube: $W_{j-1} \times CF_{j-1} = W_j \times CF_j$ (6)

Enthalpy Balance: $M_j^F \frac{d}{dt} h_j^F = U_j \times A_j \times \left(T_j^F - T_{j+1}^F\right) \Big/ \ln \frac{\left(T_j^D - T_{j+1}^F\right)}{\left(T_j^D - T_j^F\right)} - W_T \left(h_j^F - h_{j+1}^F\right)$ (7)

Overall Enthalpy Balance of Stage is given by,

$$M_j^D \times \frac{dh_j^D}{dt} + \left(h_j^V - h_j^D\right) \times \frac{dM_j^B}{d} = D_{j-1} \times h_{j-1}^D + B_{j-1} \times h_{j-1}^B - D_j \times h_j^D - B_j \times h_j^B - W_T \times \left(h_j^F - h_{j+1}^F\right) \quad (8)$$

Distillate and flashing brine temperature relation: $T_{Bj} = T_{Dj} + TE_j + EX_j + \Delta_j$ (9)

The stage pressure relationship: $\log 10 \frac{P_C}{P_j} = \frac{X}{T_j^V}\left(\left(a + b \times X + c \times X\right) / \left(d \times X\right)\right)$ (10)

Brine and Distillate tray Holdup calculation: $M_j^B = \rho_j^B \times Oh_j^B \times L_j \times V_j^B$ (11)

$$M_j^D = \rho_j^D \times Oh_j^D \times L_j \times V_j^D \quad (12)$$

2.2 Brine Heater Model

Mass Balance: $B_{BH} = W_T$ (13)

Salt mass Balance: $C_{BH} = C_R$ (14)

Enthalpy balance: $M_{BH} \times \frac{d}{dt} h_{BH} = U_H \times A_H \times \left(\left(T_{BH} - T_1^F\right) \Big/ \left(\ln \frac{T_{steam} - T_1^F}{T_{steam} - T_{BH}}\right)\right) - W_T \times \left(h_{BH} - h_1^F\right)$ (15)

$$W_{steam} \times \lambda_{steam} = U_H \times A_H \times \left(T_{BH} - T_1^F\right) \Big/ \left(\ln \frac{T_{steam} - T_1^F}{T_{steam} - T_{BH}}\right) \; B_{BH} = W_T \quad (16)$$

2.3 Blowdown splitter

$$B_D = B_{NS} - R \quad (17)$$

2.4 Reject seawater splitter:

$$C_W = W_S - F \quad (18)$$

2.5 Makeup Mixers Model

Mass balance: $W_R = R + F$ (19)

Salt Balance: $R \times C_{BNS} + F \times C_S = W_R \times C_R$ (20)

The correlations for physical and chemical properties (except the calculation of TE) and the above are taken from Rosso et al., (1996). Husain et al. (2003) also used similar correlations. Instead of an empirical correlation an NN based correlation (Tanvir and Mujtaba, 2006) is used here to calculate the temperature elevation (TE) due to salinity. Detailed development of MSF process model is found in Sowgath (2007). All symbols of the model are defined in Rosso et al. (1996) and in more recent work of Tanvir and Mujtaba (2006).

3. Optimisation problem formulation

The dynamic optimization problem (***DOP***) can be described mathematically as shown below.

$$\textbf{\textit{DOP}} \qquad \underset{T_{steam},R,C_W}{Max} \quad PR$$

$$\text{s.t.} \quad f\left(t,x,\dot{x},u,v\right)=0 \quad \text{(model equations)} \qquad [t_0,t_f] \tag{21}$$

$$\left(93\ {}^{o}C\right)\ T_{steam}^{L} \le T_{steam} \le T_{steam}^{U}\ (101\ {}^{o}C) \tag{22}$$

$$(33\ {}^{o}\mathrm{C})\ T_{seawater}^{L} \le T_{seawater} \le T_{seawater}^{U}\ (39\ {}^{o}\mathrm{C}) \tag{23}$$

$$D_N = D^* = 9\times10^5 \tag{24}$$

Subscripts/superscripts *L* and *U* refer to lower and upper bounds of the parameter. The daily time horizon is split into several zones. The dynamic seawater temperature profile is considered to be piecewise constant in each time zone. Also the stage temperatures are constrained within a narrow limit to reduce heat exchanger fouling.

4. Results and discussions

Table 1 lists all the constant parameters of the model equations including various dimensions of the brine heater and flash stages. Table 2 also shows the sample validation results of the dynamic process. There is a close agreement between the predictions of the dynamic model at steady state condition with those presented by Rosso et al. (1996).

Table 1: Constant parameters and Model validation

	A_j or A_H m^2	D_j^i or D_H^i m	D_j^o or D_H^o m	f_j^i or f_H^i $\mathrm{hm}^{2o}\mathrm{C/kcal}$	w_j, L_j or L_H m	H_j m
Brine heater	3,530	0.022	0.0244	1.86×10^{-4}	12.2	
Recovery stage	3,995	0.022	0.0244	1.4×10^{-4}	12.2	0.457
Rejection stage	3,530	0.024	0.0254	2.33×10^{-5}	10.7	0.457
W_S	T_{steam}	$T_{seawater}$	C_S	R		
1.131×10^8 kg/h	97 °C	35 °C	5.7 wt%	6.35×10^6 kg/h		

Table 2: Constant parameters and Model validation

F kg/h	B_D kg/h	W_R kg/h	W_{steam} kg/h	C_R wt/wt
5.68×10^6	4.76×10^6	1.203×10^7	1.348×10^5	6.29×10^{-2}
5.68×10^6	**4.78×10^6**	**1.203×10^7**	**1.316×10^5**	**6.27×10^{-2}**

Stage Profiles (Brine heater stage j =0; TBT = T_{B0})

Stage	B_j kg/h	D_j kg/h	C_{Bj} wt/wt	T_{Fj} °C	T_{Dj} °C	T_{Bj} °C
Brine	1.203×10^7		0.0629			89.74
heater	**1.203×10^7**		**0.0627**			**88.66**
1	1.197×10^7	5.94×10^4	0.06295	83.68	86.04	85.58
	1.197×10^7	**5.98×10^4**	**0.0632**	**83.33**	**85.75**	**86.89**
16	1.110×10^7	9.34×10^5	0.0681	38.17	39.80	41.40
	1.113×10^7	**9.04×10^5**	**0.0682**	**38.07**	**39.98**	**41.51**

The results of this work are shown in bold

In Figure 3, an external disturbance of seawater temperature is considered where it increases from 23 °C to 45 °C and T_{steam} remaining at 97 °C. Note that in reality the plant will not experience such a big step change in a short period of time. However, this case is considered to test the robustness of the dynamic model in terms of handing large step change. With the change in the seawater temperature, the plant will reach to a different steady state condition (producing less freshwater). To produce the same amount of freshwater, the steam temperature needed to be changed to 116.5 °C (Figure 3).

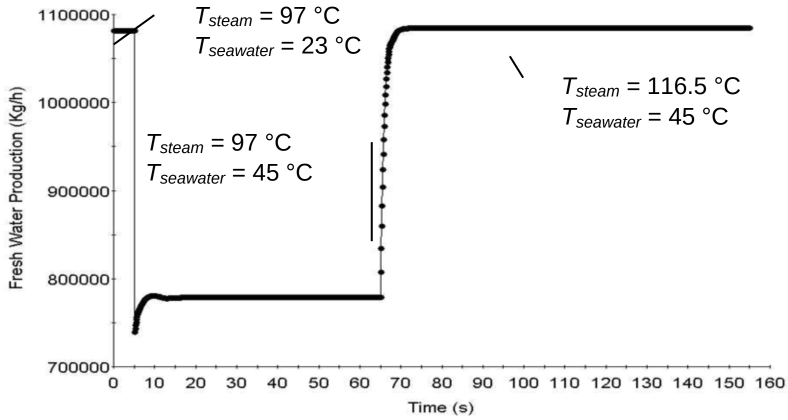

Figure 3: Dynamic Model Prediction of Fresh Water Production due to Steam Temperature Disturbance

4.1 Case study: The desired steam temperature to maintain the fixed water demand

It is assumed that during a particular day of the spring season, the seawater temperature increases from 33 (9 am in the morning) to 39 ºC (at 12 pm noon) and falls back to 33 ºC (at 3 pm in the afternoon) as shown in Figure 4. Although the temperature change will be gradual, but for the sake of convenience it is assumed that they change at discrete points as shown. It is also assumed that the steam temperature also changes at these discrete points. The purpose of this exercise is to find out optimum steam temperature at these discrete points which will be needed to off-set the change in seawater temperature while maintaining the same level of water demand and maximising the performance ratio (note, for a fixed water demand, steam temperature determines the amount of steam).

Table 2: Summary of the Optimisation Results

Run	T_{steam}	$T_{seawater}$	*PR*
1	93.96	33	11.4481
$D_N = D^* = 9\times10^5$	95.76	35	
2	95.76	35	11.5376
$D_N = D^* = 9\times10^5$	97.55	37	
3	97.55	37	11.6261
$D_N = D^* = 9\times10^5$	99.35	39	
4	99.35	39	11.5376
$D_N = D^* = 9\times10^5$	97.51	37	
5	97.51	37	11.4481
$D_N = D^* = 9\times10^5$	95.72	35	
6	95.72	35	11.3575
$D_N = D^* = 9\times10^5$	93.94	33	

The results are presented in Table 3 which clearly show that the change in steam temperature can off-set the change in seawater temperature while maintaining the fixed water demand. Also note, the PR values during the period (9 am to 3 pm) is almost constant. Note, it is assumed that the plant is operating at steady state right up to the point of changes of seawater temperature and reaches to the next steady state after 8 s of the step change in the seawater temperature (as can be seen from Figure 4). Therefore, the results only include 16 s operations prior and after the step change. Basically, the second 8s operation is dynamic (as shown in Figure 4 for TBT) during the period (9 am to 3 pm).

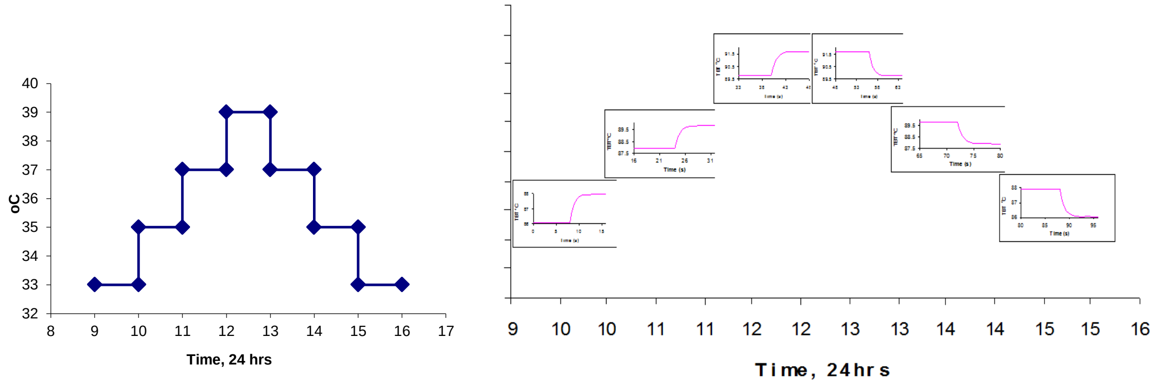

Figure 4: Seawater Temperature profile and TBT Response of the Optimised T_{steam} Profile

5. Conclusions

A detailed dynamic MSF process model describing the physical behaviour of the plant is considered here to study the impact of dynamic seawater temperature change on the performance of the process. gPROMS software package has been used to construct the model. The model included non-equilibrium effects, demister pressure drop and the brine and distillate hold up equations. The model is used within a dynamic optimisation framework to optimise the steam temperature profile subject to several step changes in seawater temperature while ensuring fixed water demand and maximum Performance Ratio. The seawater temperature profile is considered to be piecewise constant in each time zone. It clearly offers potential to explore flexible design, scheduling and operation of MSF desalination process simultaneously without compromising the freshwater demand. In future, the dynamic model will be used for control study.

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