

Modelling and Simulation of MSF Desalination Process using gPROMS and Neural Network based Physical Property Correlation

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Abstract

Multi Stage Flash (MSF) desalination plants are a sustainable source of fresh water in arid regions. Modelling plays an important role in simulation, optimisation and control of MSF processes. In this work an MSF process model is developed using gPROMS modelling tool. Accurate estimation of Temperature Elevation (TE) due to salinity is important in developing reliable process model. Here, instead of using empirical correlations from literature, a Neural Network based correlation is used to determine the TE. This correlation is embedded in the gPROMS based process model. We obtained a good agreement between the results reported by Rosso et. al. (1996) and those predicted by our model. Effects of seawater temperature ($T_{seawater}$) and steam temperature (T_{steam}) on the performance of the MSF process are also studied and reported.

Keywords: Desalination, MSF, modelling, gPROMS, NN based correlation.

1. Introduction

The technique of turning seawater into fresh water is called desalination. Multi-Stage Flash (MSF) distillation process (Fig. 1) has been used for many years and is the largest sector in the desalination industry (El-Dessouky and Hisham, 2002). An MSF process consists of three main sections: brine heater, recovery section with NR stages (flash chambers) and a rejection section with NJ stages. Seawater enters into the last stage of the rejection stages and passes through a series of tubes to remove heat from the stages. Before the rejection section seawater is partly discharged to the sea to balance the heat. The other part is mixed with the recycled brine from the last stage of the rejection section and fed before the last stage of the recovery section. Seawater is flowing through the tubes in different stages to recover heat from the stages and the brine heater raises the seawater temperature to the maximum attainable temperature (also known as Top Brine Temperature, TBT). After that it enters into the first flashing stage and produce flashing vapour. This process continues until the last stage of the rejection

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section. The concentrated brine from last stage is partly discharged to the sea and the remaining is recycled as mentioned before.

A typical MSF process model includes mass and energy balances, the geometry of the stages and physical properties which are functions of temperature and salinity. Adequate knowledge of the total heat transfer area, the length of the flash chamber, control of the corrosion and scale formation are needed for modelling, design and scale up of MSF processes. These parameters are dependent on/ inter-related with TBT (Spiegler and Liard, 1980).

Several correlations for estimating the TE exist in the literature (Bromley et al., 1974). However in this work Neural Network based correlation is used to determine the TE. The NN based correlations can be easily adapted to the new plant data and give more accurate predictions of TE compared to the empirical ones (Tanvir and Mujtaba, 2006).

2. MSF Process Model

Models for each unit operation (such as flash chamber, brine heater, splitter and mixer) are developed separately and connected via a high level modelling language using gPROMS. gPROMS is a general Process Modelling System which is capable of performing simulation, optimisation and parameter estimation of highly complex processes. It is chosen in this work because it is reliable and requires less programming knowledge (as in FORTRAN and C).

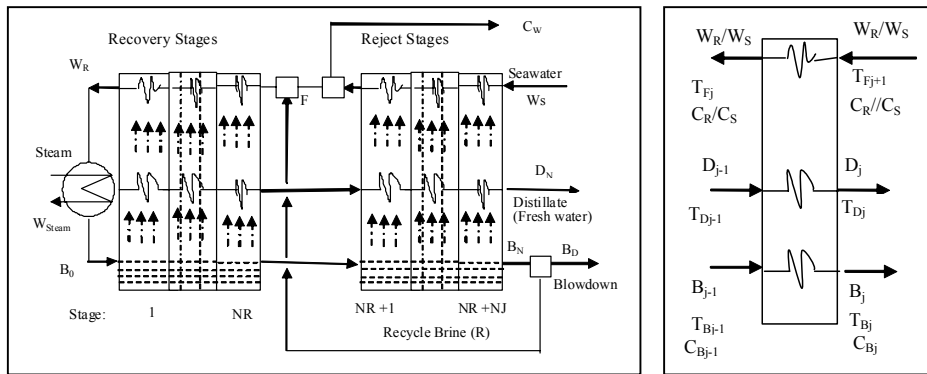


Fig.1 A Typical MSF Process and Stage j

The steady state model equations (based on Rosso et al., 1996) are given in Fig. 2 (most symbols except few are defined in the original reference). For a total number of stages $NS = NR + NJ$, the total number of equations (TNE) is: $25NS + 27$. The total number of variables (TNV) is: $18NS + 16$. Therefore, the degrees of freedom (D.F. = $TNV - TNE$) is: $7NS + 11$.

All physical property correlations shown in Fig. 2 except for TE (temperature elevation due to salinity) are taken from Hellal et al. (1986), Rosso et al. (1996) and Hussain et al. (2003). The NN based correlation for the estimation of TE is described by Tanvir and Mujtaba (2006), which was developed based on Bromley (Bromley et al., 1974) data.

Here we considered 3-layer NN architecture with 4 neurons in the hidden layer and 1 neuron (TE) in the output layer (Fig. 3). The correlation is shown in Table 1 with the weights and biases. The detailed training, validation and testing of the network is described in Tanvir and Mujtaba (2006) and the predictions of TE by NN based correlation and experimental data are compared by Tanvir and Mujtaba (2006).

Stage Model	
Mass Balance in the flash chamber:	$B_{j-1} = B_j + V_j$ $B_{j-1} C_{Bj-1} = B_j C_{Bj}$
Mass Balance for the distillate tray:	$D_j = D_{j-1} + V_j$
Enthalpy balance on flash brine:	$B_j = (h_{Bj-1} - h_{vj}) / (h_{Bj} - h_{vj}) B_{j-1}$
	$h_{vj} = f(T_{Sj})$ $h_{Bj} = f(C_{Bj}, T_{Bj})$
Overall Enthalpy Balance:	
	$W_R S_{Bj}(T_{Fj} - T_{Fj+1}) = D_{j-1} S_{Dj-1}(T_{Dj-1} - T^*) + B_{j-1} S_{Bj-1}(T_{Bj-1} - T^*) - D_j S_{Dj}(T_{Dj} - T^*)$ $- B_j S_{Bj}(T_{Bj} - T^*)$ (replace W_R for W_S rejection stage)
Heat transfer equation:	
	$W_R S_{Bj}(T_{Fj} - T_{Fj+1}) = U_j A_j X$ (replace W_R for W_S rejection stage)
	$X = \{(T_{Dj} - T_{Fj+1}) - (T_{Dj} - T_{Fj})\} / \ln \{(T_{Dj} - T_{Fj+1}) / (T_{Dj} - T_{Fj})\}$
	$U_j = f(W_R, T_{Fj}, T_{Fj+1}, T_{Dj}, D_j, D_{j-1}, L_j, f_j)$ (replace W_R for W_S rejection stage)
	$S_{Bj} = f(T_{Fj+1}, T_{Fj}, C_R)$ (replace C_R for C_S rejection stage)
	$S_{Dj} = f(T_{Dj})$ $S_{Bj} = f(T_{Bj}, C_{Bj})$
Distillate and flashing brine temperature correlation:	
	$T_{Bj} = T_{Dj} + TE_j + EX_j + \Delta_j$
Distillate and flashed steam temperatures correlation:	$TS_j = TD_j + \Delta_j$
	$TE_j = f(T_{Dj}, C_{Bj})$ $\Delta_j = f(T_{Dj})$ $EX_j = f(H_j, w_j, T_{Bj})$
Brine Heater Model	
$B_0 = W_R$ $C_{B0} = C_R$	$B_0 S_{RH}(T_{B0} - T_{F1}) = W_{steam} \lambda_S$
	$\lambda_S = f(T_{steam})$
$W_R S_{RH}(T_{B0} - T_{F1}) = U_H A_H Y$	
$Y = \{(T_{steam} - T_{F1}) - (T_{steam} - T_{B0})\} / \ln \{(T_{steam} - T_{F1}) / (T_{steam} - T_{B0})\}$	
$U_H = f(W_R, T_{B0}, T_{F1}, T_{steam}, D_H^i, D_H^o, f_H^i)$	$S_{RH} = f(T_{B0}, T_{F1})$
Splitters Model	
$B_D = B_{NS} - R$	$C_W = W_S - F$
Makeup Mixers Models	
$W_R = R + F$ $RC_{BNS} + FC_S = W_R C_R$	$W_R h_W = Rh_R + Fh_F$
$h_W = f(T_{Fm}, C_R)$ $h_F = f(T_{FNR+1}, C_F)$	$h_R = f(T_{BNS}, C_{BNS})$
Note: T* is reference temperature = 0°C	

Fig. 2 MSF Process Model

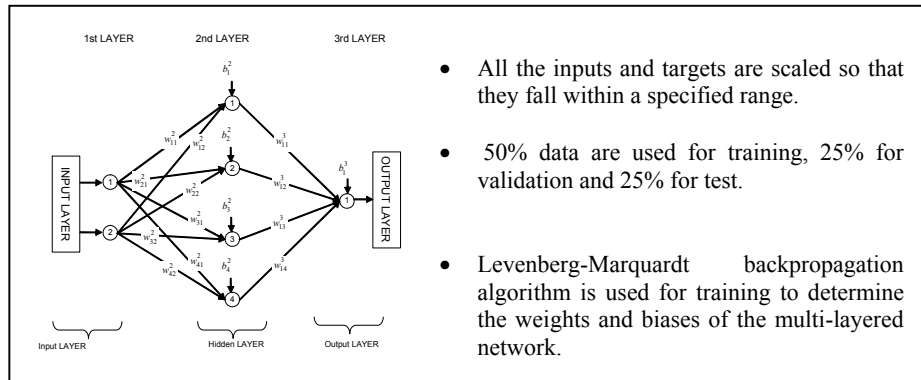


Fig.3 Neural Network Architecture for TE Estimation

Table 1. The NN based Correlation for TE (Tanvir and Mujtaba, 2006)

$TE_j = TE_{scaleup} std_TE + mean_TE$		$TE_{scaleup} = a_1^3 = w_{11}^3 a_1^2 + w_{12}^3 a_2^2 + w_{13}^3 a_3^2 + w_{14}^3 a_4^2 + b_1^3$	
$a_1^2 = \tanh(w_{11}^2 x_{scaleup} + w_{12}^2 BPT_{scaleup} + b_1^2)$		$a_2^2 = \tanh(w_{21}^2 x_{scaleup} + w_{22}^2 BPT_{scaleup} + b_2^2)$	
$a_3^2 = \tanh(w_{31}^2 x_{scaleup} + w_{32}^2 BPT_{scaleup} + b_3^2)$		$a_4^2 = \tanh(w_{41}^2 x_{scaleup} + w_{42}^2 BPT_{scaleup} + b_4^2)$	
$x_{scaleup} = (x - mean_x) / std_x$		$BPT_{scaleup} = (BPT - mean_BPT) / std_BPT$	
$std_x = 2.169$		$std_BPT = 21.02$	$std_TE = 0.352$
$mean_x = 4.037$		$mean_BPT = 91.549$	$mean_TE = 0.606$
2nd layer:			
$w_{11}^2 = 0.917$	$w_{21}^2 = 0.213$	$w_{31}^2 = 0.514$	$w_{41}^2 = -0.580$
$w_{12}^2 = 1.396$	$w_{22}^2 = 0.087$	$w_{32}^2 = -0.174$	$w_{42}^2 = 0.225$
$b_1^2 = 2.448$	$b_2^2 = -0.829$	$b_3^2 = 0.409$	$b_4^2 = -2.398$
3rd layer:			
$w_{11}^3 = 0.005$	$w_{12}^3 = 6.364$	$w_{13}^3 = 0.466$	$w_{14}^3 = -1.797$
$b_1^3 = 2.312$			
Note $BPT = T_{D1}, x \text{ (wt\%)} = C_{B1} \text{ (wt/wt)} \times 100$			

3. Results

In this work we have considered the case reported by Rosso et al. (1996). There are total of 16 stages with 13 recovery and 3 rejection stages. The specifications (satisfying the degrees of freedom) are same as those used in Rosso et al. and are shown in Table 2. The simulation results are presented in Table 3. The results (shown in plain) are in good agreement with those reported by Rosso et al. (shown in italic). The salinity and brine temperature ranges in this work are 6.29-6.82 wt% and 40-90°C. Note the NN based correlation for estimating TE was developed with salinity range 0.19-7.23 wt% and 60-120 °C. Despite the temperature range of this work being slightly outside the range of 60-120°C range, the simulation results are quite close those reported by Rosso et al. (1994) even in the temperature range 35-60°C.

Having satisfied with the model presented in this work, we have carried out further simulation to study the sensitivity of seawater temperature ($T_{seawater}$) and steam temperature (T_{steam}) on the total amount of fresh water produced (D_{NS}), Gained Output Ratio (GOR), Top Brine Temperature (TBT) and final bottom brine temperature (BBT). The results are summarised in Table 4.

With the increase of $T_{seawater}$ both TBT and BBT increase for a given $T_{steam} = 97$ C (Cases 1-3). As the terminal temperature difference decreases, for a given design of the plant (heat transfer area, etc.) the amount of heat removal decreases. This consequently reduces the amount of distillate produced per stage, thus reducing the total amount of freshwater. The corresponding reduction of the steam flow rate (W_{steam}) keeps the GOR almost constant. This simulation clearly shows that due to seasonal variation, more freshwater will be produced during winter (Case 1) than in summer (Case 3).

For a given seawater temperature, $T_{seawater} = 45$ C, with the increase of T_{steam} , the terminal temperature difference increases. For a given design of the plant (heat transfer area, etc.) the amount of heat removal therefore increases. This consequently increases the amount of distillate produced per stage and the total amount of freshwater (Cases 4-6). A corresponding increase of GOR is thus noticed. Note, to maintain the supply of

freshwater in summer at the winter level, there has to be an increase in T_{steam} from 97°C to 116.5°C (compare Case 1 and Case 5). To sustain the high temperature operation this might have a knock-on effect on the capital investment.

Table 2. Constant Parameters and Input Data

	A_j / A_H	D_j^i / D_H^i	D_j^o / D_H^o	f_j^i / f_H^i	$w_j / L_j / L_H$	H_j
Brine heater	3530	0.022	0.0244	1.86×10^{-4}	12.2	
Recovery stage	3995	0.022	0.0244	1.4×10^{-4}	12.2	0.457
Rejection stage	3530	0.024	0.0254	2.33×10^{-5}	10.7	0.457
W_s	T_{steam}	$T_{seawater}$	C_s	R	C_w	
1.131×10^8 kg/h	97°C	35 °C	5.7 wt%	6.35×10^6 kg/h	5.62×10^6 kg/h	

Table 3: Summary of the Simulation Results

F kg/h	B_D kg/hr	W_R kg/hr	W_{steam} kg/hr	C_R wt/wt		
$5.68*10^6$	$4.75*10^6$	$1.203*10^7$	$1.188*10^7$	$6.29*10^{-2}$		
$5.68*10^6$	$4.75*10^6$	$1.203*10^7$	$1.188*10^7$	$6.29*10^{-2}$		
Stage Profiles (Brine heater stage j =0)						
Stage	B_j kg/h	D_j kg/h	C_{Bj} wt/wt	T_{Fj} °C	T_{Dj} °C	T_{Bj} °C
0	1.203E+07		6.29E-02			90.01
	$1.203E+07$		$6.29E-02$			89.74
1	1.197E+07	57238.2	6.32E-02	83.79	86.15	86.15
	$1.197E+07$	59403.0	$6.32\ E-02$	83.33	85.75	86.79
2	1.191E+07	115214.2	6.35E-02	80.87	83.28	84.35
	$1.191E+07$	118730.0	$6.36\ E-02$	80.41	82.87	84.01
12	1.131E+07	715074.6	6.69E-02	49.31	51.97	53.15
	1.131E+07	719700.0	6.69E-02	49.27	51.93	53.24
16	1.110E+07	930882.7	6.82E-02	38.19	39.84	41.24
	$1.110E+07$	934410.0	$6.82\ E-02$	38.07	39.98	41.51

4. Conclusions

Here, gPROMS modelling tool has been used to model an MSF process. A Neural Network based correlation developed earlier (Tanvir and Mujtaba, 2006) for estimating TE is embedded within the gPROMS environment. The simulation results using the new model are in good agreement with the published results. NN based correlation predicts TE very well even slightly outside the range of training. The model is then used to study the sensitivity of two important operating parameters: the seawater temperature which is subject to seasonal variation, and the steam temperature in the brine heater which controls TBT of the process (indirectly controlling the design of the process). The

results show that the steam temperature plays an important role to maintain the production rate of freshwater at different seasons. However, this may be at the expense of costly design.

Table 4. Effect of $T_{seawater}$ and T_{steam} on D_{NS} , GOR , TBT , BBT

Case	$T_{seawater}$	D_{NS}	W_{steam}	GOR	TBT	BBT
1	23	1.09E+06	1.41E+05	7.73	88.6	30.3
2	35	9.31E+05	1.19E+05	7.82	90.1	41.2
3	45	7.88E+05	1.02E+05	7.72	91.0	50.2
T_{steam}						
4	111.0	1.01E+06	1.21E+05	8.29	103.8	51.5
5	116.5	1.09E+06	1.29E+05	8.48	108.8	52.0
6	121.0	1.16E+06	1.35E+05	8.64	112.9	52.5

Gained Output Ratio (GOR)=Total Fresh water produced/Amount of Steam Needed = D_{NS} / W_{steam}

Nomenclature

B_j	brine flow leaving stage j, kg/h	R	Recycle stream flow rate, kg/h
B_D	Blow down mass flow rate, kg/h	T_{Bj}	Temperature of flashing brine leaving stage j, °C
C_{Bj}	Brine concentration, wt/wt	T_{Dj}	Temperature of distillate leaving stage j, °C
C_W	Rejected seawater flow rate, kg/h	T_{Fj}	Seawater temperature leaving stage j, °C
C_S	Seawater salt concentration, wt/wt	W_s	Seawater mass flow rate, kg/h
C_R	Seawater salinity in the recovery stages, wt/wt	W_R	Seawater flow in the recovery section, kg/h
D_j	Distillate flow from stage j, kg/h		
F	Make-up seawater flow rate, kg/h		

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