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Generic Model Control (GMC) in Multistage Flash (MSF) Desalination

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ABSTRACT

Multistage Flash Desalination (MSF) is currently facing an enormous challenge in cutting of the cost: within the last few years, the MSF experienced a gradual decline in investment compared to other techniques of desalting water and thus, a significant improvement is required to remain attractive for capital investors. Improved process control is a cost effective approach to energy conservation and increased process profitability. In this work, a dynamic model is presented using gPROMS model builder to optimize and control MSF process. The Proportional Integral Derivative Controller (PID) and Generic Model Control (GMC) are used successfully to control the Top Brine Temperature (TBT) and the Brine Level (BL) in the last stage at different times of the year. The objectives of this study are: firstly, to obtain optimum TBT and BL profiles for four different seasons throughout the year by minimizing the Total Seasonal Operating Cost (TSOC); secondly, to track the optimum TBT and BL profiles using PID and GMC controllers with and without the presence of constraints; thirdly, to examine how both types of controllers handle the disturbances which occur in the plant. The results are promising and show that GMC controller provides better performance over conventional PID controller to handle a nonlinear system.

Keywords: MSF Desalination, Dynamic model, Optimization, PID Control, GMC Control

1. Introduction

The lack of potable water in most of countries of the world is one of everyday challenge; therefore highest priority should be given in the efforts toward solving this global problem. Due to the limitations of the underground water, low rainfall, rapid economic growth, etc., in several regions of the world, MSF is used to convert saltwater by evaporation to potable water or make-up water that is free of impurities. MSF accounts for approximately 22% of commercial desalination worldwide (Miller et al. 2014). However, MSF has higher yields than other desalination methods, such as multi-effect desalination (MED) and Reverse Osmosis (RO) separation (Darwish, 2014). Moreover, the capability of coupling the MSF plant to a power generation plant as the heat source makes the process increasingly important for future drinking water and power production.

However, desalination plants are large and complex. They are also energy-and cost intensive and above all, crucial to life support in several regions of the world. Consequently, desalination plant must meet high standards of performance, including optimality, cost effectiveness, reliability, and safety. Many of these criteria can be satisfied by improved design and control.

Most industrial plants are non-linear in nature; the complexity of their non-linearity varies according to the physical function of each process. MSF desalination is a highly complex nonlinear process (Ismail, 1998; Ali et al, 1999 and Lior et al, 2012); however, its non-linearity is represented in some operation conditions such as limitation on the brine temperature at the brine-heater outlet. Furthermore, the need for continuous monitoring of liquid levels in the flashing chambers is necessary to avoid loss of efficiency due to blow-through or loss of boiling due to flooding in the flash chambers. Therefore, an efficient and accurate control system in the plant to maintain the operation at optimum conditions is required

Most of the MSF plants are currently operated under conventional PID controller due to its simplicity and well recognition by the industry (Al-Gobaisi et al. 1991). However, PID controller is linear and cannot efficiently control highly sophisticated systems which contain nonlinear variables. Moreover, the tuning of the PID parameters is being the main concern by engineers due to the time consuming and inefficiency. Despite of a lot of work to improve the tuning of PID parameters, there is no adequate single method to obtain optimum values for these parameters. Nevertheless, due to the change of the operating conditions of the MSF, the fixed tuning of PID controller for one condition would not be optimal due to change in sea water temperature seasonally and variable water demand and thus, new optimum values of PID parameters are required which can be consider as time consuming (Al-Gobaisi et al. 1994). The availability of powerful computer tools opened the way to implement the advanced process control (APC) strategies.

A number of researches have been conducted in the past decades to implement APC strategy in the MSF desalination process. Maniar and Deshpande (1996) applied Constrained Model Predictive Control (CMPC) for MSF process. The manipulated variables for the controllers were calculated by solving an optimization problem with respect to the operating constraints. Though the authors obtained reasonable results, the nonlinearity of MSF process cannot be controlled well using linear CMPC. Later, Ali et al. (1999) utilized a reduced model to implement a robust control of MSF process using Nonlinear Model Predicted Control (NLMPC) which was able to drive the plant to its steady state with less computational time. Dewei et al. (2012) proposed a Cascaded Quadratic Dynamic Matrix Control (QDMC) as one of the MPC strategies for a Reverse Osmosis (RO) desalination process. Compared to PID control, the results revealed that the QDMC outperform the traditional PID control. Although it was developed four decades ago, Fuzzy Logic Controller (FLC) remains to have a lot of attention due to its ability to control very complex systems (Alatiqi et al,. 1999). Jamshidi et al. (1996) designed and implemented fuzzy controllers for MSF process to control TBT. A genetic algorithm was applied to fuzzy control of a brine heater unit in MSF plant. The simulation results of the controlled TBT showed a significant improvement in convergence to the desired set point and reducing oscillations and overshoot. Ismail et al. (1996) combined a set of fuzzy rules to introduce a controller that look like Proportional-Integral-Derivative (PID-like FLC). The controller was then introduced to MSF process to control TBT. Ismail

(1998) studied the capability of Fuzzy Model Reference Learning Control for the TBT. In comparison with the conventional PID and direct fuzzy logic, the results showed the outperformance of the learning system over the other two types. For the same purpose of controlling TBT, Olafsson et al. (1999) designed and applied simple fuzzy control to brine heater in MSF process. In most of their study cases, the results showed that FLC can perform better or equally well as the conventional PID controller.

Neural Network System (NNs) is another technique used as APC to handle complex and nonlinear process. Ali et al. (2015) provided an excellent review on the application of NN based control (state observers) in many engineering systems. After successful implementation of NN techniques as optimization control strategy for seawater-desalination solar-powered membrane distillation unit by Porrazzo et al. (2013), Tayyebi and Alishiri (2014) proposed nonlinear inverse model control strategy based on neural network for MSF desalination plant. Using three-layer feed forward neural network, three loops were designed for controlling the TBT, the brine level in the last stage and salinity.

Generic Model Control (GMC) is a well-known advanced control technique that has been used widely in the past and was developed by Lee and Sullivan (1988) as a result of the intense desire to develop a model that can handle nonlinear processes like most of the chemical processes. Cott and Macchietto (1989) applied GMC strategy as controller to track the reactor temperature set point. Vega et al. (1995) applied GMC controller experimentally and by simulation to a batch cooling unseeded crystallization process to control crystallizer temperature. Aziz et al. (2000) used GMC to design a controller for a batch reactor to track the optimal temperature profiles. Ghasem et al. (2003) implemented GMC controller to the two-phase model of a non-isothermal fluidized bed catalytic reactor to control the temperature inside the reactor by tracking new set point and handling the disturbance. In tracking the optimal temperature set point profile of batch reactor, Arpornwichanop et al (2005) applied GMC algorithm to drive the temperature of the batch reactor to follow the desired profile. Mujtaba et al. (2006) coupled GMC with NNs as controller to estimate the heat release due to exothermic reaction. Karacan et al. (2007) proposed multivariable generic model control (MGMC) to control the top and bottom product temperatures of the packed distillation column. Ekpo and Mujtaba (2008) used GMC controller in batch polymerisation of methyl methacrylate to track the set point optimal temperature profile with neural networks as an online heat release estimator for the system. Kamesh et al. (2014) used GMC to track a set point of reactor temperature of an industrial multiproduct semi-batch polymerization reactor.

The aforementioned publications used GMC algorithm to control the temperature in their systems. However, GMC is used widely to control other type of variables such as pH, concentration and purity. For instant, Sousa et al. (2004) proposed GMC-fuzzy algorithm for the pH control of the enzymatic hydrolysis of cheese whey proteins. Kathel and Jana (2010) implemented GMC algorithm in two different forms, namely real and ideal GMC, to control a high-purity reactive batch distillation column. Du et al. (2013) applied GMC algorithm in sewage processing to control the concentration of dissolved oxygen based on the hybrid model. Fu and Liu (2015) implemented GMC controller in heat integrated air separation column to control the purity of the Nitrogen and Oxygen products.

From the foregoing, the GMC has been proved to be simple, robust and strategic in controlling various types of process parameters, hence, the decision to use it to control the TBT and BL in MSF plant.

There is no known use of GMC as a controller strategy in MSF plants. In this work therefore, the GMC control strategy is designed and introduced to the MSF process to control and track the set points of the two most important variables in the MSF plant; namely the output temperature of the brine heater (TBT) and the Brine Level (BL) in the last stage. To do so, an optimization problem is solved first to obtain different values for TBT and BL set points for four different seasons throughout the year. For a comparison purpose, the PID and PI are used to control the TBT and BL respectively. Note, all the past work on the control of MSF process restricted to one particular season (for a single seawater temperature). Also, they were restricted to track a set point change without simultaneously disturb any other systems' parameters. We have relaxed both of these in this work.

2. Process description

The MSF process is similar to multicomponent distillation, but there is no exchange of material between the countercurrent streams. The MSF process is an evaporating and condensing process in vacuum, where the vacuum changes from one stage to the next and the evaporation temperature decreases from the first to the last stage. The process is based on evaporation of a strong saline seawater (brine) and condensation of the generated vapor. The MSF unit can be divided into two sections in Once-Through MSF process (MSF-OT); a Brine Heater Section (BR) and Heat Recovery Section (HRS). For brine recirculation MSF process (MSF-BR), however, extra section is added called Heat Rejection Section (HRJ). The process itself is well known and can be found in the literature (El-Dessouky and Ettouney, 2002). Here, the discussion will be limited to MSF-BR process only. A typical MSF-BR process is shown in Figure 1. The process consists of essentially a brine heater and a number of flashing and condensing stages connected in series. The seawater (Ws) flows through the condenser tubes and enters at temperature (Ts) and heated up to a temperature (T_1) in the rejection section by condensation of product water vapour gained by flashing of seawater. Part of the leaving seawater is rejected to the sea (C_W) and the other part is used as make-up (F) to be fed into last stage. The recirculation brine (Rec) leaving the last stage at (T_5) is fed to the heat recovery section where it is heated to a temperature of (T_2). In the brine heater, the preheated seawater is further heated to highest possible temperature (T_3) called the TBT. From where it passed through the flashing stages at a lower pressure, partly flashes into vapour which is condensed on the condenser tubes and is collected in the distillate tray across the stages. The brine then leaves the recovery section at temperature (T_4) and rejection section at (T_5) where part of the brine goes to blow down (B_D) and the rest is recirculated (Rec) (Soliman, 1981). Note, many alternative configurations of the MSF process can be generated depending on the way the seawater is fed and brine is recycled (El-Dessouky and Ettouney, 2002). The two loops of controllers that are under investigation in this work are shown in this Figure 1.

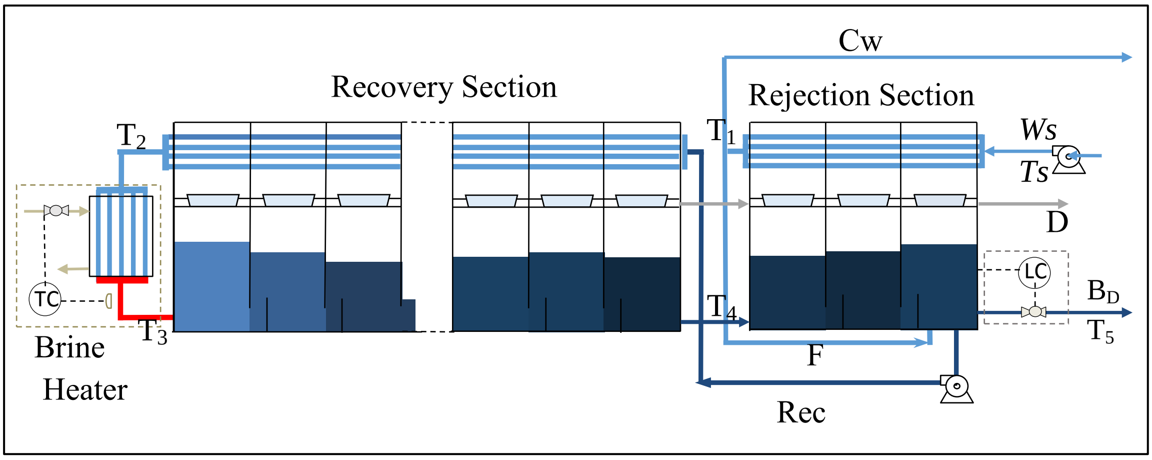

Figure 1: Schematic of MSF-BR process

3. Mathematical model

To achieve the objectives of this study, a detailed dynamic model of MSF process is required. The dynamic model is developed and implemented using gPROMS model builder. The model is based on Reddy et al. (1995) and Alfulaij et al. (2011). The actual data used to validate this model were obtained from Alasfour and Abdulrahim (2009) of Azzour desalination plant. The Azzour desalination plant is located in Kuwait; it has 24 stages with capacity of 6 MGD per unit and has eight units with total output of 48 MGD (Al-Shayji et al., 2005). The model has been already run dynamically and in steady state, and results were examined against actual data by Alsadaie and Mujtaba (2014).

Stage Model

Mass balance of the brine

$$\rho_B A_S \frac{dL_B}{dt} = B_{in} - B_{out} - V_B \tag{1}$$

Salt balance

$$\rho_B A_S L_B \frac{dX_B}{dt} = B_{in} \times (X_{Bin} - X_{Bout}) + V_B X_{Bout} \tag{2}$$

Mass balance of the distillate

$$\rho_D A_D \frac{dL_D}{dt} = D_C + D_{in} - D_{out} \tag{3}$$

Vapour mass balance

$$\rho_V A_S \frac{d(L_s - L_B)}{dt} = V_B + V_{in} - D_C - V_{out} \tag{4}$$

Energy balance of the brine

$$\rho_B A_S L_B \frac{dh_B}{dt} = B_{in} \times h_{Bin} - h_{Bout} \times (B_{in} - V_B) - V_B \times h_{VB} \tag{5}$$

$$h = Cp \times (\Delta T) \tag{6}$$

$$Cp = f(X_B, T) \tag{7}$$

Energy balance of the distillate

$$\rho_D A_D L_D \frac{dh_D}{dt} = D_C \times h_{DC} + D_{in} \times h_{Din} - D_{out} \times h_{Dout} \tag{8}$$

Energy balance of the vapour space

$$\rho_V A_S (L_S - L_B) \frac{dh_V}{dt} = V_B \times h_V + V_{in} \times h_{Vin} - D_C \times \lambda_v - V_{out} \times h_{Vout} \tag{9}$$

Distillate and flashing brine temperature correlation:

$$T_B = T_V + BPE + NEA + \Delta T_{DEM} \tag{10}$$

Overall energy balance around tube bundles

$$\rho_S V_{Tube} \frac{dh_F}{dt} = [D_C \times \lambda_V + V_{in} \times (h_{Vin} - h_{Vout})] + \quad W_R \times (h_{Fin} - h_{Fout}) \tag{11}$$

Heat transfer equation:

$$W_R \times (h_{Fin} - h_{Fout}) = U \times A \times \frac{(T_{Fout} - T_{Fin})}{ln\left[\frac{(T_V - T_{Fin})}{(T_V - T_{Fout})}\right]} \tag{12}$$

Total distillate

$$D_{Total} = \sum_{i=1}^{n} D(i) \tag{13}$$

<u>*Brine Heater Model*</u>

Mass and salt balance

$$W_R = B_0; \qquad X_R = X_{B0} \tag{14,15}$$

Energy balance of the cooling brine

$$\rho_B V_{brine} \frac{dh_{B0}}{dt} = U_h \times A_h \times \frac{(T_{B0} - T_{F1})}{ln\left[\frac{(T_{steam} - T_{F1})}{(T_{steam} - T_{B0})}\right]} - W_R (h_{B0} - h_{Fin}) \tag{16}$$

Enthalpy balance of the condensing steam:

$$W_{steam} \times \lambda_{steam} = U_h \times A_h \times \frac{(T_{B0} - T_{F1})}{ln\left[\frac{(T_{steam} - T_{F1})}{(T_{steam} - T_{B0})}\right]} \tag{18}$$

<u>*Last Stage, N*</u>

Mass balance of the brine

$$A_S \rho_B \frac{dL_{BN}}{dt} = B_{in} + F - B_{out} - V_B - Rec \tag{19}$$

B_{out} in equation (19) is B_D in Figure 1.

$$Rec = B_0 = W_R \tag{20}$$

Salt balance

$$\rho_B A_S L_B \frac{dX_B}{dt} = B_{in} \times (X_{Bin} - X_{Bout}) + F \times (X_f - X_{Bout}) \tag{21}$$

Energy balance in brine pool

$$\rho_B A_S L_B \frac{dh_B}{dt} = B_{in} \times h_{Bin} - h_{Bout} \times (B_{in} - V_B) - V_B \times h_{VB} + F \times h_{mk} - Rec \times h_{out} \tag{22}$$

The material and energy balances for distillate and vapour are similar to those for single stage. In rejection stages, W_R is replace by W_S and X_R is replaced by X_S.

4. Optimization problem

The wide difference in seawater temperature during the day (also between summer and winter seasons) has great impact on TBT and BL, consequently, product rate and plant performance are affected. The seawater temperature depends on the locality and the time of the year and it can be varies between 15 ^{o}C and 35 ^{o}C (Hawaidi and Mujtaba, 2010). Darwish et al, (1996) reported that it can be as low as 10 ^{o}C in Kuwait. At low temperature, its mass flow rate has to be reduced to achieve reasonable flashing brine temperature in the bottom stages. However, the decrease in the cooling seawater flow rate can result in a decrease in its velocity as low as lower than the acceptable minimum (about 1.5 m/s) (Darwish et al, 1996). For this reason, most MSF plants operate in summer and winter mode, when the set point of the intake sea water temperature varies between 25 ^{o}C in the winter mode and 32 ^{o}C in the summer mode (Alatiqi et al. 1999).

For fixed operating conditions, the MSF plants produce more fresh water in winter (low sea water temperature) than in summer. However, this production pattern goes counter to the demand of fresh water (Hawaidi and Mujtaba, 2011). Tanvir and Mujtaba (2008) minimised the operating cost by optimizing the number of stages based on seasonal variation of the sea water temperature. For fixed fresh water production and TBT, Hawaidi and Mujtaba (2010) studied the effect of sea water temperature on the operating cost of the MSF process. Hawaidi and Mujtaba (2011) conducted an optimization study to demonstrate the optimum design and operation of MSF process to meet the variable demand of fresh water through the day and the year at fixed TBT.

For control purpose, an optimization study is conducted to obtained different optimum values for TBT and BL based on four different seasons. Based on seawater temperature profile presented by Hawaidi and Mujtaba (2010), a four different values of the sea water temperature are considered; 20 ^{o}C, 28 ^{o}C, 32 ^{o}C, and 24 ^{o}C for winter, spring, summer and autumn respectively (Figure 2). To obtain different values of the TBT, a fixed number of stages and fixed fresh water product are considered. Moreover, to obtain different values of

BL, more constrains are introduced to maintain the brine level in all stages at reasonable level, and thus optimal values for BL are obtained for each season.

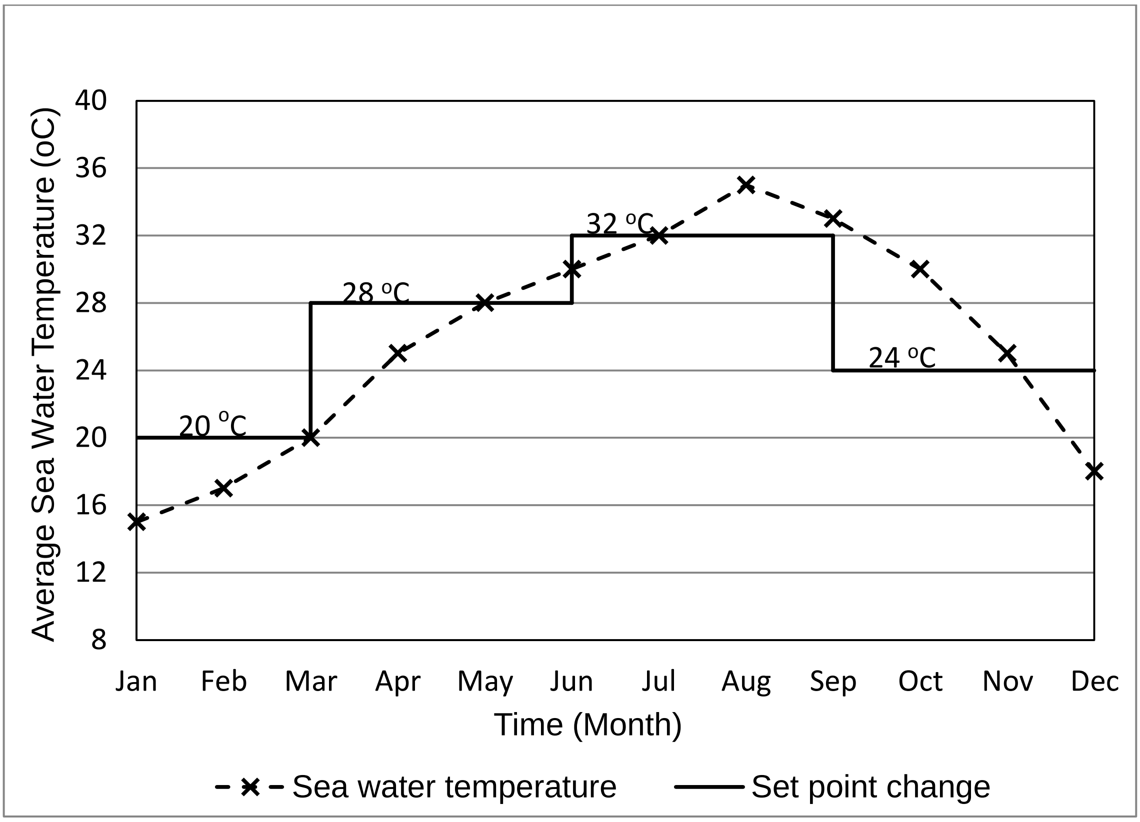

Figure 2: Variations of sea water temperature and set point profiles for four seasons (Hawaidi and Mujtaba, 2010)

For the given design configurations; fixed number of stages, fixed fresh water demand, fixed steam temperature and four values of the intake sea water temperature to determine the optimum *TBT*, *BL*, *Rec* and W_S by minimizing the Total Seasonal Operating Cost (TSOC).

The Optimization Problem (OP) is described as follows;

$$\underset{TBT,\ BL,\ Rec,,\ Ws}{\text{OP}} \qquad \text{Min} \qquad \text{TSOC}$$

s.t. $f(x,u,v) = 0$ (model Eqs)

$$D_{end} \quad = \quad D_{end}^{*}$$

$$(85\ ^{\circ}\mathrm{C}) \quad \leq \quad TBT \quad \geq \quad (98\ ^{\circ}\mathrm{C})$$

$$(0.3\ m) \quad \leq \quad BL \quad \leq \quad (0.8\ m)$$

$$\left(11500\,\frac{ton}{hr}\right) \quad \leq \quad Rec \quad \leq \quad \left(17200\,\frac{ton}{hr}\right)$$

$$\left(7600\,\frac{ton}{hr}\right) \quad \leq \quad W_S \quad \leq \quad \left(13600\,\frac{ton}{hr}\right)$$

Where D_{end} is the total capacity of the plant and D^{*}_{end} is the fixed water demand (=1296 ton/hr). The boundary values of *Rec* and W_S are chosen based on the minimum and maximum allowable values of the water velocity in the condenser tubes between 1.5 and 2.3 m/s (Helal, 2003)

The objective function equation (TSOC) is obtained from Hawaidi and Mujtaba (2011) and defined total annual cost (TAC) as

$$\text{TAC (\$/year) = CPC + STC + TOC} \tag{23}$$

Where CPC is the annualized capital cost, STC is the storage tank cost and TOC is the total operating cost. Since the CPC and STC are function of the plant configuration and constant for all seasons, then the only variable cost here is the TOC. Hawaidi and Mujtaba (2011) defined the TOC as following:

$$TOC\ (Total\ Annual\ Operating\ Cost, \$/year) = C_1 + C_2 + C_3 + C_4 + C_5 \tag{24}$$

Where

$$C_1\ (Steam\ cost, \$/year) = 8000 \times W_{steam} \times [(T_{steam} - 40)/85] \times 0.00415 \tag{25}$$

$$C_2\ (Chemical\ cost, \$/year) = 8000 \times [D_{end}/1000] \times 0.025 \tag{26}$$

$$C_3\ (Power\ cost, \$/year) = 8000 \times [D_{end}/1000] \times 0.109 \tag{27}$$

$$C_4\ (Maintenance\ cost, \$/year) = 8000 \times [D_{end}/1000] \times 0.082 \tag{28}$$

$$C_5\ (Labour\ cost, \$/year) = 8000 \times [D_{end}/1000] \times 0.1 \tag{29}$$

The TSOC can be defined as following:

$$TSOC = TOC/4 \tag{30}$$

More details on the calculations of TOC can be found in Hawaidi and Mujtaba (2010, 2011).

5. Controller strategy

For safety purpose, most MSF plants have many control loops to maintain steady state and overcome the instability caused by the start-up of the plant or failure in one of the plant components. Maniar and Deshpande (1996) and Ismail (1998) mentioned nine controlled variables with nine corresponding manipulated variables as the main process variables to be controlled. Al-Gobaisi et al. (1994) mentioned that most existing MSF plants could be controlled by 4 to 6 primary loops. However, in these studies two main control loops were TBT control loop and BL control loop as without these two loops the plant cannot be controlled at all. In this study we also implemented GMC control in these two control loops.

1. Top brine temperature (TBT). The temperature of the recirculation brine after it is heated by the low pressure steam in the brine heater. It plays an important role in describing the performance of MSF and has direct effects on the distillate production

and the levels in each flash chamber. It can be used to control the whole plant in addition to load control. This means for each plant production, there is a certain top brine temperature which depends on the seawater inlet temperature

2. Last stage brine level (BL): The brine levels in the flash stages are quickly affected by the steam supply temperature or flow rate (Husain et al., 1994). Brine levels in all stages should be high enough to seal the interstage orifices and prevent blow-through. However, the high BL increases the thermodynamic non-equilibrium losses and should be low enough to ensure less equilibration losses. An adjustable level controller is required with high sensitivity over the permissible range of BL. This controller is one of the most important control loops in the MSF plant since the level in all stages is controlled by adjusting the BL in the last stage (Darwish et al., 1996).

5.1 Proportional Integral Derivative (PID) Controller

The PID controller is widely used and recommended for a variety of problems. It can be used for many industrial systems. The controller parameters can be tuned by using trial and error methods, or any of the classical tuning techniques such as Zeigler Nicholas. For many process control problems, good results can be achieved by tuning PI, or PID using conventional methods, which rely on the knowledge and skill of the control engineer However, due to the change in conditions of the MSF plant during its operation, tuning PID parameters are always considered as time consuming and it is a quite challenging.

The simplest form of PID controller can be represented by:

$$C(t) = k_c\left(e(t) + \frac{1}{\tau_i}\int_0^t e(t)dt + \tau_D\frac{de(t)}{dt}\right) \tag{31}$$

Where k_c is the proportional gain, τ_i is the integral time, τ_D derivative time constant, e is the error (controller input), and C is the controller command (controller output).

5.1.1 Tuning of the PID Controller

As mentioned above, different methods can be used to tune the PID controller parameters. The most common method is the integral performance criterion. In this work, an optimization based method is used to minimize the Integral Absolute Error (IAE), the Integral Time Absolute Error (ITAE) and Integral Square Error (ISE) and the PID parameters (k_c, τ_i, τ_D) are optimized to give minimum error. Since initial values of PID parameters are required to conduct the optimization problem, Ziegler-Nichol's method is used to obtain the initial values for PID parameters.

The optimization problem (OP) is described as following

OP	Min	IAE, ITAE and ISE
k_c, τ_i, τ_D	*error*	

subject to:

$$-100 \leq k_c \leq 100$$

$$0.0 \leq \tau_i \leq 100$$

$$0.0 \leq \tau_D \leq 100$$

The results of the optimization problem for TBT and BL loops are presented in Table 2. Figure 3a and Figure 3b show the performance of both controllers, TBT and BL respectively, using the three types of optimization criterion (ISE, IAE and ITAE). The optimum values from best method are used later in the control comparison. It is to be mentioned that two optimization functions are used here. One is to optimize the parameters of the TBT controller loop and another is to optimize the parameters of the BL controller loop.

5.2 Generic Model Control (GMC) Strategy

Since its development by Lee and Sullivan in 1988, there has been growing interest in the use of GMC, which has been demonstrated to have certain robustness for a wide range of process nonlinearity against model mismatches. GMC is relatively easy to implement and does not require linearizing the nonlinear process (Aziz et al., 2000).

The GMC control algorithm can be written as following;

$$\frac{d\dot{y}}{dt} = K_1(y_{sp} - y) - K_2 \int (y_{sp} - y)dt \quad (32)$$

Where y is the measured variable and y_{sp} is the desired value of the control variable. Similarly to PI controller, the first expression of the above equation k_1 $(y_{sp}$-$y)$ is required to bring the process from a large distance towards steady state, but some offset would exist. The second expression $k_2 \int (y_{sp}-y)dt$ however, is required to eliminate the offset of the controller. The values of k_1 and k_2 are tuning parameters to obtain the desired response. More details of the model can be found in Lee and Sullivan (1988).

In the brine heater of MSF process, the dynamic model equation relating the TBT as controller variable to the steam flow rate (Ms) as a manipulated variable can be written as;:

$$\frac{d(T_{B0})}{dt} = \frac{(M_s \times \lambda) - W_R \times Cp \times (T_{B0} - Tc_{in})}{M_{bh} \times Cp} \quad (33)$$

Here, the T_{B0} is the TBT, W_R is the brine flow rate, Cp is the heat capacity of the brine, Tc_{in} is the temperature of the brine entering the brine heater, λ is the latent heat released by the condensate steam and M_{bh} is the brine mass hold up inside the brine heater tubes. To solve for the control, the actual output rate is set equal to the desired output rate. In other words, setting Equation (32) equal to Equation (33) and substituting T_{B0} for y and T_{B0_sp} for y_{sp}.

$$\frac{(M_s \times \lambda) - W_R \times Cp \times (T_{B0} - Tc_{in})}{M_{bh} \times Cp} = k_1\left(T_{B0\_sp} - T_{B0}\right) + k_2 \int \left(T_{B0_{sp}} - T_{B0}\right) dt \quad (34)$$

Solving for the manipulated variable, Ms, the following equation can be obtained.

$$M_s = \frac{1}{\lambda} \times \begin{pmatrix} M_{bh} \times Cp \times \left[K_1\left(T_{B0\_sp} - T_{B0}\right) + K_2 \int \left(T_{B0\_sp} - T_{B0}\right)dt\right] \\ +\left[W_R \times Cp \times \left(T_B - Tc_{in}\right)\right] \end{pmatrix} \tag{35}$$

Ms gives the amount of steam flow rate required to control the outlet temperature of the brine heater.

Similarly, the above procedure can be followed to implement the GMC method to control the brine level in the last stage. First, process model equation relating the brine level, L_B, as controller variable to the brine flow rate leaving the last stage (*Bout*) as manipulated variable must be defined. Equation (36) is the material balance equation in the last stage, and can be used here to calculate the change of the brine level, L_B, in the last stage.

$$\frac{dL_B}{dt} = \frac{(B_{in} + F - B_{out} - V_B - Rec)}{A_S \times \rho_B} \tag{36}$$

Where B_{in} is the brine flow rate leaving the previous stage, *F* is the makeup flowrate fed to the last stage, *Bout* is the blow down flow rate leaving the last stage, V_B is the vapour leaving the brine pool, and Rec is the recycle brine flow rate. To solve for the control, Equation (36) must be equalised to Equation (32) and substituting L_B for y and L_{B_sp} for y_{sp}.

$$\frac{\left(B_{j-1} + F - B_{out} - D - Rec\right)}{A_S \times \rho_B} = K_1\left(L_{B\_sp} - L_B\right) + K_2 \int \left(L_{B\_sp} - L_B\right)dt \tag{37}$$

Solving for the manipulated variable, *Bout*, Equation (38) can be obtained.

$$\begin{aligned} B_{out} &= B_{j-1} + F - D - Rec \\ &\quad - \left[A_S \times \rho_B \times \left(K_1\left(L_{B\_sp} - L_B\right) + K_2 \int \left(L_{B\_sp} - L_B\right)dt\right)\right] \end{aligned} \tag{38}$$

Bout gives the amount of blow down flow rate required to maintain the BL in the last stage at the desired level.

5.2.1 Tuning of the Generic Model Controller

Lee and Sullivan (1988) provided a figure that outlines the relation between two variables, ξ and τ. Tuning GMC can be obtained by choosing a better combinations of ξ and τ. The choices should be reasonable and require understanding of the system's natural dynamic response. By choosing reasonable values of ξ and τ, the two tuning parameters k_1 and k_2 are obtained using Equations (39 and 40).

$$k_1 = {}^{2\xi}/_{\tau} \tag{39}$$

$$k_2 = {}^{1}/_{\tau^2} \tag{40}$$

It is important to mention that different values of k_1 and k_2 are obtained for different control loops. More details of the procedure in choosing ξ and τ can be found in Lee and Sullivan (1988).

6. Results and discussions

Simulations with optimization of the MSF process for four different seasons, optimization of PID controller parameters, TBT and BL controls were carried out using gPROMS builder model. First, the MSF process was optimized at fixed plant capacity and four different values of sea water temperature by minimizing the TSOC. For the sake of stability, other variables such as (Rec) and the intake sea water flow rate (W_S) were relaxed to fluctuate for limited values. Since the steam is coming from different source, its temperature is fixed and only the steam flow rate valve is varied to achieve the optimum TBT. The results of the optimization are shown in Table 1. The table also includes the optimum brine recycle and intake sea water flow rate at fixed capacity for four different seasons. Therefore, the operator has to change these values to their next values after every season. It should be mentioned that the optimum values for TBT and BL for four seasons are developed for control purpose and cannot be relied on to make accurate performance. More parameters must be considered to draw final design evaluation.

Table 1: Optimum values for TBT & BL in four seasons.

Season	Seawater Temp set point (^oC)	TBT (^oC)	BL (m)	Rec (ton/hr)	Ws (ton/hr)
Winter	20	88.64	0.358	13889.27	10207.91
Spring	28	92.10	0.429	14607.22	12704.94
Summer	32	94.09	0.472	15026.22	12895.81
Autumn	24	90.06	0.433	14256.94	12533.11

The main objective of this study is to evaluate the performance of GMC controller comparing to conventional PID controller by tracking the set points change of TBT and BL respectively. The PID controllers are introduced to the model and their parameters are tuned (Table 2).

Table 2: Optimum PID parameters for TBT and BL control loops.

Interval	Criterion	Parameters of PID Controller		
		kc	T_i	t_D
TBT	ISE	1.2873	0.0052	0.1481
	IAE	2.01	0.014	1.04
	ITAE	1.6776	0.062	0.976
BL	ISE	5.44	0.193	15.308
	IAE	30.41	1.182	1.16
	ITAE	39.89	0.06	1.435

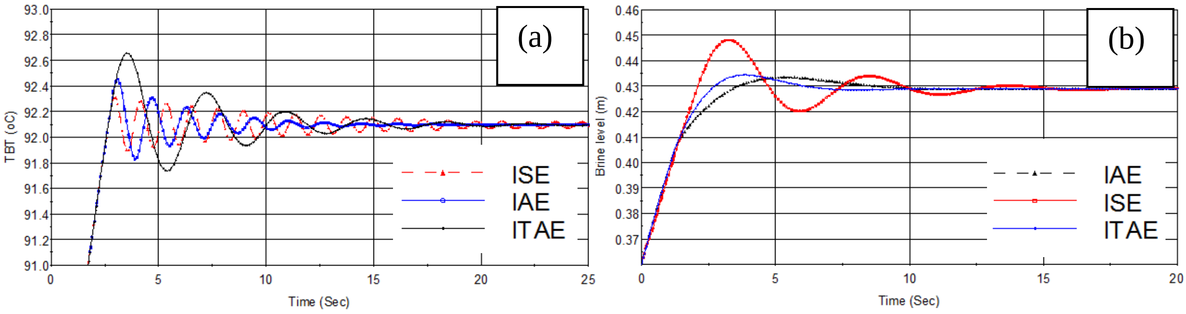

Figure 3: Step response of the optimally tuned PID parameters (a) TBT loop (b) BL loop.

To select the best technique that used to minimize the error and thus giving optimum values of PID parameters, the results presented in Table 2 are plotted in Figure 3a and 3b respectively (Only for Spring operation conditions). It is to be mentioned here, the optimum values obtained by optimization techniques were very aggressive in some cases. As it can be seen from Figure 3a, the values obtained for TBT loop using ISE and IAE criteria are very aggressive and take large time to settle down while these from ITAE, though have overshooting, seem to be close to optimum and less aggressive. For, BL loop, however, the values obtained using ITAE seem to be less aggressive and giving very smooth curve. Thus the optimum values of PID parameters obtained by ITAE criteria are considered to be our choice for both loops. This choice applies for all seasons.

For tuning GMC parameters for TBT loop, Cott and Macchietto (1989) recommended a value of 10 for ξ to eliminate the overshoots. However, Lee and Sullivan (1988) mentioned that the selection of GMC parameters depends on the system's natural dynamic response. In this work, the value of 10 for the ξ that gives less overshoots is selected. τ is calculated using the graphical method proposed by Lee and Sullivan (1988) which gives 16 sec for TBT loop and 8 sec for the BL loop.

For each controller loop, three case studies were performed to examine the performance of each type of controller in the set points tracking, disturbance and constraint handling.

Top Brine Temperature Loop (TBT)

Case 1: Set point tracking

Figure 4 presents the control performance of the PID and GMC controller for tracking the set point change of TBT based on different seasons. For each season's data, the model run for 40 seconds to reach steady state before changing the new set of data for the next season. For reader interpretation convenience, the results of process variables and manipulated variables were plotted together in one figure (Figure 4).

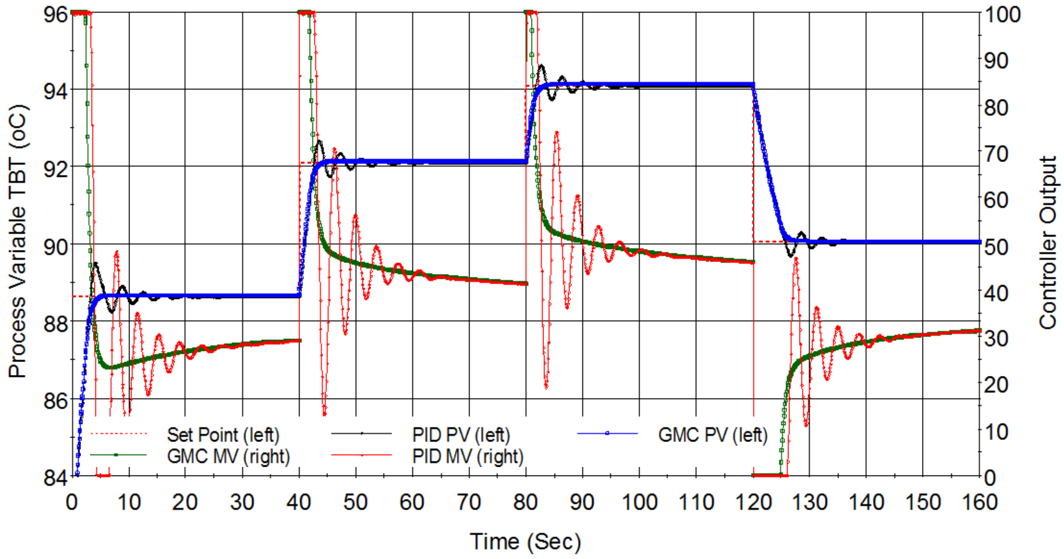

Figure 4: Tracking the TBT set points for four different seasons using GMC & PID controllers

In all cases, GMC controller was performing smoothly and reach the set point in less time. The PID controller, on the other hand, expressed oscillatory response more than GMC before returning to the set point while the GMC controller did not reveal any sluggish response and move smooth towards the new set point and provide better performance over PID in tracking the set point. Similar behaviour can be observed for the manipulated variables (steam flow rate). For PID, the steam flowrate looks unstable in attempt to bring the process variable (TBT) back to the set points for all seasons. However, the steam flow rate behaviour for the GMC controller was smooth and stable while controlling the process variable.

Case 2: Disturbance

Disturbance normally occurs in MSF plants due to the pumps or valves failure. In order to examine the capability of the controller in handling the disturbance, a change in the brine recycle flow rate was introduced in this case at a regular interval of 50 s by increasing its value 6%, decreased 14% and then increased by 8%. The process was assumed that it runs in the autumn season when the disturbance occurred. The recycle flow rate was chosen as the disturbance because it affects the TBT and BL at the same time. Figure 5 shows the performance of both controllers in handling the disturbance. As it can be seen, the GMC controller acts vary fast and provide better performance in returning the temperature to steady state. Also as expected, a perfect GMC (with no modelling error) should not have significant change in the PV when disturbances enter the system. However, the PID controller exhibits some oscillatory response and couldn't reach the set point fast and takes larger time to reach steady state. The manipulated variables reacted simultaneously as their process variables. When increasing the recycle brine flow rate by 6%, the steam flow rates increased to provide enough heat to keep the TBT constant. Similarly when the recycle flowrates decreased by 14%, the steam flow rates dropped to maintain constant TBT. For PID controller, the behaviour of the steam flow rate follows the same behaviour of the process variable with some oscillatory response while the steam flow rate using GMC controller behaves smoothly and fast to keep in the TBT constant.

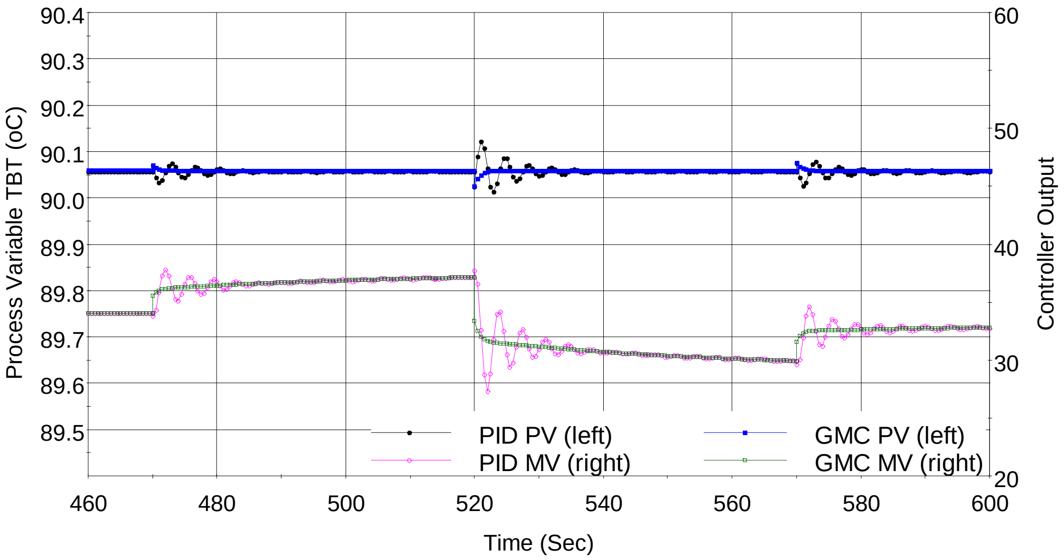

Figure 5: Handling the disturbance to control the TBT using GMC & PID controllers

Case 3: Constraint handling

The availability of steam depends on external source and thus it is limited to a certain amount. Here, similar to the first case, the set points of the TBT was changed based on the four different seasons however, the steam flow rate was assumed to be limited and hit the lower and higher limits to bring the controlled variable to its set point. As it can be seen in Figure 6, the set point was raised in spring season and thus more steam than required was needed to raise the TBT to its new set point. Thus, the steam hit the constraint of 100% for short time resulting in delay of the PID controller to reach the set point compared to the first case. The same results can be seen when the set point was further raised to 94.09 ^{o}C in summer. This is due to the reason that when the set point was increased, the controller sent signal to the steam valve to fully open. However, due to the lack of available steam PID controller struggle to bring the process back to its steady state. In autumn, when the set point was changed to 90.06 ^{o}C, the steam flow rate was constrained by 0% and thus again the controller took large time in attempt to bring the TBT to its new set point. In comparison with the GMC controller, it seemed that GMC controller performs similarly in handling the constraints because the availability of the steam that control the process and thus both controllers behave similarly and slowly. Figure 6 shows that the steam hit the constraint of 100% and 0% for the same time as it was shown for PID. However, when the available steam is adequate for the appropriate temperature, the GMC controller performs faster and smoothly and exhibit less oscillatory or sluggish response compared to PID controller when experienced large overshooting in particular when the set point was further increased in summer period.

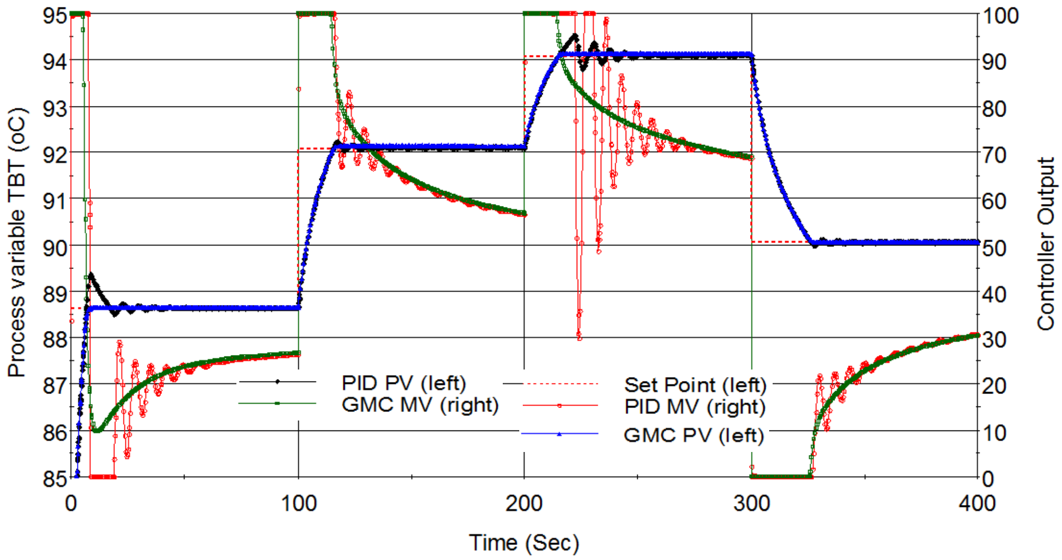

Figure 6: Tracking the TBT set points using GMC and PID controllers with constraints.

Last Stage Brine Level Loop (BL)

Case 4: Set point tracking

Although, there was no large difference in the BL set points for different seasons, the difference was quite reasonable to examine the controller's performance. Figure 7 shows that the set points were changed based on four seasons. The PID and GMC controllers were implemented to track the new set points. In all intervals (Season interval), the GMC controller over performed the PID controller and reached the set point faster. The PID showed slight sluggish response and took some time to reach the set point. When the set points were increased from winter to spring and again from spring to summer, the GMC controller reached the set point at the same time with PID, however, while PID continues slugging, the GMC remains constant and kept the BL stable. The reason of the both controller crossed the set point at the same time is that the tuning of GMC parameters were tuning based on the time that PID cross the set point as it was mentioned before. The behaviour of the manipulated variables (Blow down) were identical to the performance of the process variables (brine level). The manipulated variable of GMC was smooth while the manipulated variable of the PID experienced slight overshooting to bring the level of the stage back to its set point.

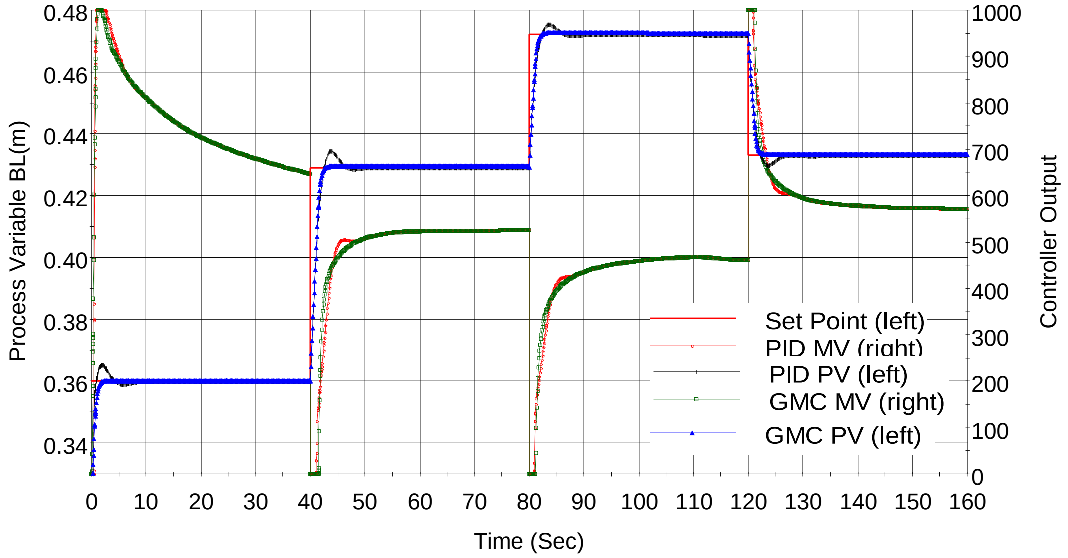

Figure 7: Tracking the BL set points for four different seasons using GMC & PID controllers

Case 5: Disturbance

Similar to the case 2 in TBT loop, the same disturbance of the brine recycle was introduced to the process and the behaviour of both controllers were observed. Both loops (TBT and BL) work simultaneously and any set points change or disturbance affects both loops at the same time. Thus, the same step change in the brine recycle was introduced to BL loop. As it can be seen in Figure 8, the GMC controller over performed the PID controller in bringing the process back to its steady state very fast. While PID controller showed some overshoots before reaching the set point, the GMC work perfectly in handling the disturbance and look like no change occurred to the process.

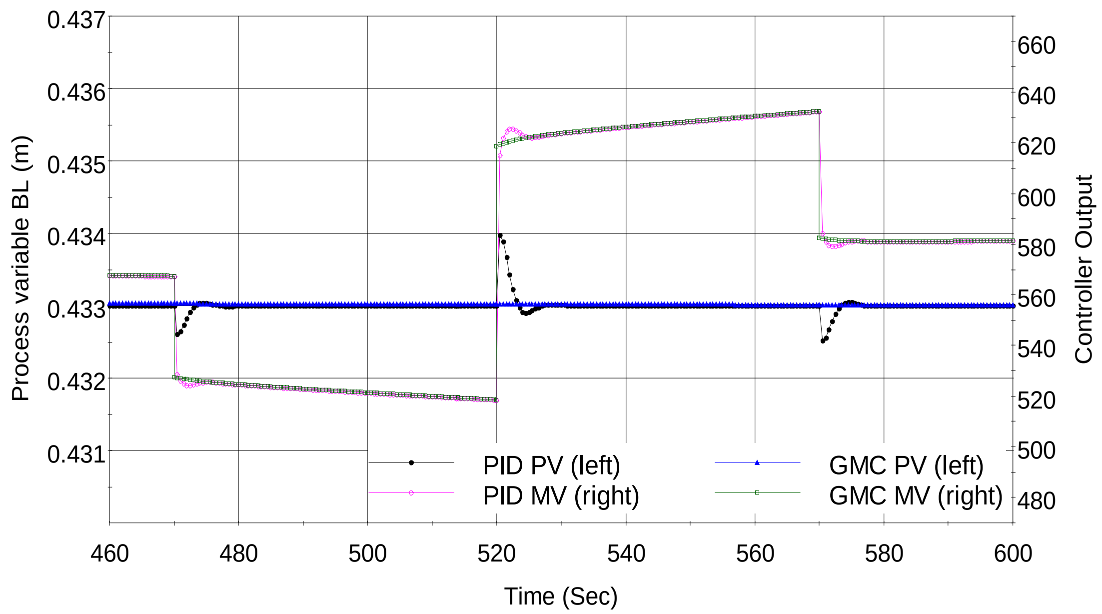

Figure 8: Handling the disturbance to control the TBT using GMC & PID controllers

Case 6: Constraint handling

The valve of the blowdown flow rate is assumed to open and close to limited positions to study the performance of the controllers under the constraints. Thus, the set points of the BL was changed based on the four different seasons and the valve position was assumed to be limited and reached the lower and higher limits to bring the controlled variable to its set point. As it can be seen from Figure 9, though both controllers worked well in controlling the process, GMC looks better in bringing the process to steady state fast at the start-up of the plant. Both valves were hitting 0% and 100% to bring the process steady, however, the valve controlled by GMC started to be stable first to maintain the BL constant. When the set point of BL was increased from 0.36 m in winter to 0.429 m in spring and raised again in summer up to 0.742 m, the valve of the blowdown were closed completely. Due to the constraints, the valve position reached its lower limit in attempt to increase the BL to its set points. Here, both controllers. PID and GMC look behave similarly in controlling the process well. Again, in the final season (autumn) when the set point was changed from 0.472m to 0.433 m, the valve position reached the higher limit for few seconds to bring down the BL to its new set point. GMC controller worked better here in autumn (last interval) in reaching the set point fast. Regarding to the manipulated variable behaviour, the manipulated variables for both controllers behave similarly as it was in Figure 7, however, PID manipulated variable react few seconds behind GMC manipulated variable. Despite their close performance in controlling the BL, the GMC has more stability over PID controller and could easily accommodate all the process changes.

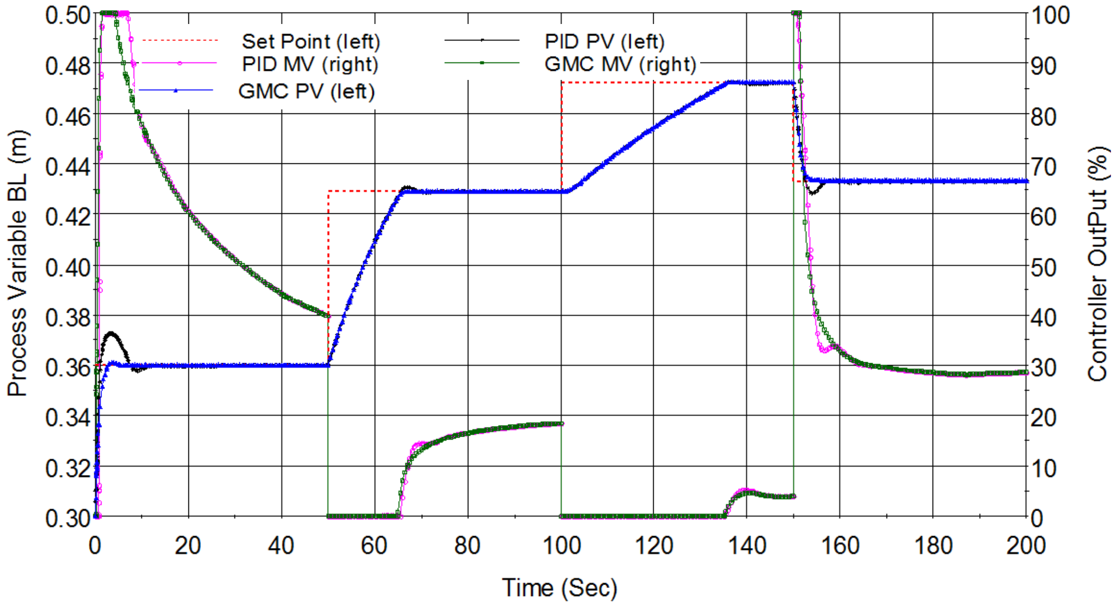

Figure 9: Tracking the BL set points using GMC and PID controllers with constraints.

7. Conclusions

The work presented in this paper focused on the implementation of GMC control in MSF desalination plants. Since most MSF plants are operated under conventional PID control, the proposed GMC control can improve the control process in MSF plants. To carry out the control process, detailed dynamic model of MSF process was developed and implemented using gPROMS model builder. Two controller loops, namely TBT and BL, were designed to investigate the performance of GMC controller. For each loop, three cases were carried out; tracking the set points without constraints, tracking the set points with constraints and handling the disturbance. Different values for TBT and BL set points were selected for four seasons in the year based on optimisation process. The disadvantage of PID controller is its linearity and time consumption in tuning its parameters. However, GMC is easy to use and can handle nonlinear systems. Also, the tuning of the GMC parameters is very simple.

In comparison to the PID controller, the results indicated that the GMC is powerful and robust tool in controlling MSF plants and outperformed the PID in all cases. In handling the disturbance for example, the GMC control the process easily without showing any oscillatory or overshoots. In TBT loop, although both controllers reached the set points nearly at the same time, the GMC reached the set points with less overshoots and more smoothly. However, in BL loop, GMC controller appeared to be fast and more robust in controlling the level with and without the present of the constraints and over performed the PID controller.

In the BL loop, it is important to mention that both controllers were not just used to track the set point but to overcome the change of other variables such as the recycle flow rate, intake sea water temperature and intake sea water flow rate. Here, the GMC controller looks even better in tracking the set points. While the PID controller exhibits some oscillatory, the GMC controller reaches the set point fast and remain constant for the whole period. This behaviour was monitored for all four seasons.

Most importantly, it is the tuned procedure of the two controllers. While PID parameters took large time to be tuned and waste of time, the GMC parameters were tuned fast and easily based on known plant speed and graphical method.

Although most of the applications of the GMC algorithm were in controlling the temperature, here, the GMC was used successfully to control the level of the brine in MSF as well as the temperature of the brine heater and has revealed its controllability to handle nonlinear system under different set points change with and without constraints.

Nomenclature

A_S - Stage area (m^2)

A	- Heat transfer surface area of a stage (m^2)
A_h	- Heat transfer surface area of the brine heater (m^2)
A_D	- Distillate tray area (m^2)
B_0	- Flashing brine mass flow rate leaving brine heater (kg/s)
B_{in}	- Brine inlet flow rate to a stage (kg/s)
B_{out}	- Brine outlet flow rate from a stage (kg/s)
BPE	- Boiling point elevation (^oC)
C_p	- Specific heat at constant pressure (kJ/kg ^oC)
D_C	- Total condensate flow in a stage (kg/s)
D_{in}	- Distillate flow rate to a stage (kg/s)
D_{out}	- Distillate flow rate to a stage (kg/s)
D_{total}	- Total distillate product flow rate 9kg/s)
h_{Bo}	- Enthalpy of flashing brine leaving the brine heater (kJ/kg)
h_{Bin}	- Enthalpy of flashing brine entering a stage (kJ/kg)
h_{Bout}	- Enthalpy of flashing brine leaving a stage (kJ/kg)
h_{DC}	- Enthalpy of condensate distillate around tube bundle (kJ/kg)
h_{Din}	- Enthalpy of distillate entering a stage (kJ/kg)
h_{Dout}	- Enthalpy of distillate leaving a stage (kJ/kg)
h_{Fin}	- Enthalpy of cooling water entering the brine heater (kJ/kg)
h_{NCGs}	- Enthalpy of NCGs leaving the flashing brine in a stage (kJ/kg)
h_{VB}	- Enthalpy of vapour below demister in a stage (kJ/kg)
h_V	- Enthalpy of vapour around cooling tubes (kJ/kg)
h_{Vin}	- Enthalpy of vapour entering from previous stage (kJ/kg)
h_{Vout}	- Enthalpy of vapour leaving a stage (kJ/kg)
L_B	- Height of the brine (m)
L_D	- Height of the distillate (m)
L_s	- Height of the stage (m)
MV	- Manipulated variable
NEA	- Non-equilibrium allowance (^oC)

PV	- Process variable
TBT	- Top brine temperature (^oC)
T_{Bo}	- Temperature of flashing brine leaving the brine heater (^oC)
T_{Bin}	- Temperature of flashing brine entering a stage (^oC)
T_B	- Temperature of flashing brine leaving a stage (^oC)
T_{F1}	- Temperature of cooling brine entering the brine heater (^oC)
T_{Fin}	- Temperature of cooling brine entering a stage (^oC)
T_{Fout}	- Temperature of cooling brine leaving a stage (^oC)
T_{steam}	- Steam temperature (^oC)
T_V	- Temperature of flashed vapour in the vapour space (^oC)
U_h	- Overall heat transfer coefficient in the brine heater ($kW/m^2\ ^oC$)
V_{brine}	- Volume of the cooling water inside the brine heater (m^3)
V_B	- Vapour release flow rate from brine in a stage (kg/s)
V_{in}	- Vapour flow rate entering a stage (kg/s)
V_{out}	- Vapour flow rate leaving a stage (next stage or vent) (kg/s)
V_{tube}	- Volume of the cooling water inside the tube bundle (m^3)
W_R	- Cooling brine flow in the heat recovery stages (kg/s)
W_S	- Cooling seawater flow in the heat rejection stages (kg/s)
W_{steam}	- Steam flow rate (kg/s)
X_{Bin}	- Salt concentration in the brine entering a stage (ppm)
X_{B0}	- Salt concentration in the brine leaving brine heater (ppm)
X_{Bout}	- Salt concentration in the brine leaving a stage (ppm)
X_R	- Salt concentration in the cooling brine in the recovery section (ppm)
X_S	- Salt concentration in the cooling brine in the rejection section (ppm)

Greek letters

ΔT	- *Temperature drop (^oC)*
ΔT_{Dem}	- Temperature drop through demister (^oC)
ρ_B	- Brine density (kg/m^3)

ρ_D	- Distillate density (kg/m^3)
ρ_V	- Vapour density (kg/m^3)
ρ_S	- Cooling water density (kg/m^3)
λ_V	- Latent heat of vapour in a stage (kJ/kg)
λ_{steam}	- Latent heat of steam (kJ/kg)

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