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Improvement of Performance Indicators of Multistage Flash Desalination Plant using Genetic Algorithms

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Abstract

Multistage flash (MSF) desalination plants are energy intensive and it is, therefore, important to use operating parameters that lead to reduction of energy consumption and consequently reduction of fresh water production cost. In this study, an optimization of operating parameters of an actual MSF-BR desalination plant was performed using as objective the improvement of the main plant performance indicators. Four decision variables related to the operating conditions were chosen for optimization, i.e., the temperature of the heating steam, the cooling seawater flow rate, the brine recycle flow rate, and the make-up flow rate. These decision variables were subjected to constraints to ensure that maximum and minimum bounds were adhered. A multi-objective function that consists of the main plant performance indicators, i.e., the thermal performance ratio, the specific cooling water flow rate, the specific recirculating brine flow rate, and the specific feed flow rate, were used in the optimization problem. In order to achieve this we have used a multi-objective solver (*gamultiobj*) available in the MATLAB optimization toolbox. This solver uses genetic algorithms for finding the Pareto-optimal solutions. The optimization results reveal that a significant improvement of the performance indicators can be obtained if we use the optimal operating points given by solving the optimization problem.

Keywords: *Multistage flash; Performance indicators; Matlab optimization solver; Genetic algorithms; Pareto-optimal solutions.*

Nomenclature

A	Regression coefficient
M	mass flow rate (kg/s)
M	specific flow rate
PR	thermal performance ratio
T	temperature (°C)
X	*salinity (ppm)*

Subscripts

d	distillate
cw	cooling seawater
f	feed
hs	heating steam
R	recirculating

1. Introduction

Increase in population and standards of living together with climate disruption and water pollution, are diminishing the quantity of naturally available freshwater while the demand is increasing continuously. Indeed, freshwater consumption is increasing at the rate of 4-8 % per year, 2.5 times the population growth [1]. Thus, global water shortages will become so catastrophic over the next 25 years that two in three people on the planet will face regular depletion of water supplies [2]. As more than 97% of the world's water is saline [3], desalination technology is vital for sustaining human habitation in many parts of today's world. In fact, the volume of the water desalination industry has rapidly increased over the past five decades. The number of operating desalination units in the early 1960s was less than 10, and

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increased to over 13000 in 2010. At present, the word production of desalination water exceeds 100×10^6 m^3/d. Furthermore, the installed capacity increases annually by an average of more than 10%. Multi-stage flash (MSF) desalination process (Fig. 1) has been used for decades for making freshwater from seawater and is now the largest sector in seawater desalination [4].

MSF desalination industries are facing the challenges to improve their market shares and reduce the cost of fresh water produced, while they are energy intensive. In addition, since construction costs of MSF plants are competitive in the global economy, thus the only way to achieve the ambitious goal of reducing the cost of water produced is by reducing the operational cost. The most important parameters that control the operational cost of fresh water produced, called plant performance indicators, are [4]:

- The thermal performance ratio, which is the ratio of distillate flow rate to the heating steam flow rate,

$$PR = M_d/M_{hs} \tag{1}$$

- The specific cooling seawater flow rate, which is the ratio of cooling water flow rate to distillate flow rate,

$$sM_{cw} = M_{cw}/M_d \tag{2}$$

- The specific recirculating brine flow rate, which is the ratio of recirculating brine flow rate to distillate flow rate,

$$sM_r = M_r/M_d \tag{3}$$

- The specific feed flow rate, which is the ratio of feed flow rate to distillate flow rate,

$$sM_f = M_f/M_d \tag{4}$$

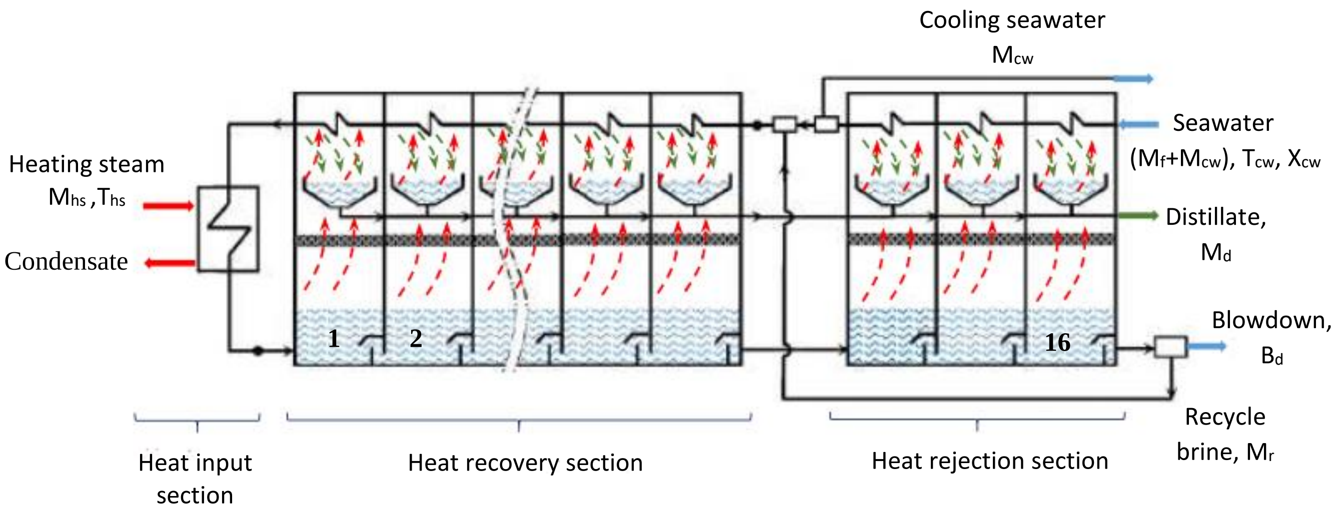

Figure 1. Schema of brine recycle multistage flash desalination process (MSF-BR)

In this study, the optimization of operating variables, in steady-state phase, of MSF-BR desalting plant is considered. The objective functions for the optimization are selected among the plant performance indicators. Thus, during this optimization, the thermal performance ratio (PR) is maximized while the specific cooling water flow rate (sM_{cw}), the specific recirculating brine flow rate (sM_r), and the specific feed flow rate (sM_f) are minimized. The decision variables are the make-up flow rate (M_f), the cooling seawater flow rate (M_{cw}), the brine recycle flow rate (M_R) and the steam temperature (T_{hs}). They are the steady-state operating variables when we conduct performance calculations. An efficient solver optimization tool of Matlab software (*gamultiobj*) using genetic algorithms was used to resolve the four-objective optimization problem.

2. Description of the MSF-BR process

Figure 1 shows a schematic diagram of the MSF-BR desalination plant. It consists of three sections: heat rejection, heat recovery, and heat input. The heat rejection and heat recovery sections consist of a number of flash chambers (stages) connected in series.

Seawater enters the plant through the heat rejection section. Before entering the recovery section, most of the seawater, called cooling water, is discharged into the sea to remove the surplus thermal energy from the plant. The recirculating brine, which is formed by mixing part of the feed seawater (make-up) and a large mass of brine from the last stage of the plant, is circulated through the condensers of the heat-recovery section. In this section, the stream is preheated in the condenser units by absorbing the latent heat of the distillate vapor. In the heat-recovery section, the brine gets heated as it passes through the tubes from one stage to another by exchanging the thermal energy from the flashing vapor in each stage. Thus, the heat released by the condensation of vapor is used to heat the recirculating brine. Passing through the last stage, the water enters the brine heater, where its temperature is raised to the saturation temperature (*i.e.* TBT) for the system's pressure. Next, the saturated brine enters the first stage of the heat-recovery section. As the brine runs into the first stage, it will become superheated and flashed-off to give vapor as a result of pressure reduction. The vapor then passes through the demisters, where the salt carried with the vapor is removed, condenses on the cooling tubes, and collected as distillate in the distillate tray. The process is then repeated all the way down the plant as both brine and distillate enter the next stage at a lower pressure. The distillate is finally collected, disinfected, and treated for pH and hardness before going to storage vessels.

3. Plant description

The configuration investigated in this work refers to data of real plant located at Al-Khobar in Saudi Arabia. It uses a cross-tube arrangement with recirculating brine, and consists of 10 MSF-BR desalting units. The study concerns the operation of the plant during summer mode. Each plant includes 13 stages in the heat recovery section and 3 stages in the heat rejection section. The other unit plant's characteristics are [5, 6]:

- *Heat input section (brine heater):*
  -Number of tubes 3800.
  -Tube size 22.0 mm (inside diameter) × 1219 mm (thickness) × 12.2 m (length).
  -Heat transfer area 3530 m^2.
  -Tube material Cu–Ni (70–30).
  -Fouling factor 0.160 m^2K/kW.

- *Heat recovery section:*
  -Number of stages 13, stages 1–13.
  -Stage width 12.2 m.
  -Number of tubes 4300.
  -Tube size 22.0 mm (inside diameter) × 1219 mm (thickness) × 12.2 m (length).
  -Heat transfer area 3995 m^2.
  -Tube material Cu–Ni (90–10).
  - Height of brine level 0.457 m.
  -Fouling factor 0.120 m^2K/kW.

- *Heat rejection section:*
  -Number of stages 3, stages 14–16.
  -Stage width 10.7 m.
  -Number of tubes 3800.
  -Tube size 24.0 mm (inside diameter) × 0769 mm (thickness) × 10.7 m (length).
  -Heat transfer area 3530 m^2.
  -Tube material Titanium.
  -Height of brine level 0.457 m.
  -Fouling factor 0.020 m^2K/kW.

- *Feed seawater characteristics:*
  -Temperature 37°C.
  -Salinity 56 000 ppm.

4. Optimization problem formulation

The optimization problem to be addressed in this paper is described as follows

Given: The design and some operating characteristics of the MSF-BR unit,

Optimize: Heating steam temperature (T_{hs}), recycled brine flowrate (M_R), rejected seawater flowrate (M_{cw}), and make-up seawater flowrate (M_f).

So as to

Maximize: Thermal performance ratio (f_1).

Minimize: Specific cooling seawater flow rate (f_2), specific recirculating brine flow rate (f_3), and specific feed flow rate (f_4).

Subject to: Inequality constraints on optimization variables.

Four objective functions are simultaneously optimized to obtain a set of solutions that reduces operating costs, which comprise the vapor cost in the heater, pumping costs, and feed pretreatment costs. Indeed, at higher performance ratio (f_1), lower amount of the heating steam is used, and the reduction of the specific flow rate of cooling water (f_2) reduces the specific power consumption (consumption par unit distillate) of the cooling water-pumping unit. In addition, the reduction of the specific recirculating brine flow rate (f_3) reduces the specific power consumption of the recirculating brine-pumping unit, and the reduction of the specific feed flow rate (f_4) reduces the specific power consumption of the feed pumping unit and the specific consumption of antisacale chemicals.

The optimal solution space is reduced by adding inequality constraints. Upper and lower bounds on the decision variables are imposed according to the operational considerations [7]. In this regard, T_{hs} cannot be raised above an upper value due to scaling problems essentially in the brine heater. A lower bound on T_{hs} should also be imposed, because too much reduction of T_{hs} causes a reduction of the top brine temperature (T_{b0}) which can cause the pressure difference between the ejector and the vapor zone in the stage to become insufficient, which in turn causes an incomplete extraction of non-condensable gases, followed by instability due to the impossibility of maintaining the vacuum and possible vapor-side corrosion problems. Similarly, limits must be imposed on M_{cw}, M_R and M_f. A lower limit must be fixed to avoid scaling problems caused by a low velocity of brine in the tubes of the brine heater or the condensers. In addition, if (M_f+M_R) is low, sealing between flash chambers may not be fulfilled. As a result, the operation of the plant will be unstable and operation will be inefficient. On the other hand, a high value of (M_f+M_R) can cause distillate contamination because flooding can occur. The upper limits are also imposed to avoid erosion of brine heater and condensers tubes. Literature recommends that the brine velocity inside tubes in the heat recovery, heat rejection and heat input section should lie between 1.5 and 3 m/s [7]. Table 1 shows the bounds of the operating variables used in this study and which meet the requirements we have mentioned.

Table 1. Bounds of the operating variables [7]

Operating variables	Lower limit	Upper limit
T_{hs} (°C)	93	115
M_{cw} (kg/s)	1500	3000
M_R (kg/s)	1500	3000
M_f (kg/s)	1500	3000

The optimization problem (OP) can be described mathematically by

$$\text{(OP)} \quad \min_{x_1(T_{hs}),\, x_2(M_{cw}),\, x_3(M_r),\, x_4(M_f)} F = \begin{cases} f_1(x_1,x_2,x_3,x_4) = -\mathrm{PR} = -M_d(x_1,x_2,x_3,x_4)/M_{hs}(x_1,x_2,x_3,x_4) \\ f_2(x_1,x_2,x_3,x_4) = \mathrm{sM_{cw}} = x_2/M_d(x_1,x_2,x_3,x_4) \\ f_3(x_1,x_2,x_3,x_4) = \mathrm{sM_r} = x_3/M_d(x_1,x_2,x_3,x_4) \\ f_4(x_1,x_2,x_3,x_4) = \mathrm{sM_f} = x_4/M_d(x_1,x_2,x_3,x_4) \end{cases}$$

$93°C \le x_1 \le 115°C$
$1500\ \text{kg/s} \le x_2 \le 3000\ \text{kg/s}$
$1500\ \text{kg/s} \le x_3 \le 3000\ \text{kg/s}$
$1500\ \text{kg/s} \le x_4 \le 3000\ \text{kg/s}$

The determination of expressions of M_d (x_1,x_2,x_3,x_4) and $M_{hs}(x_1,x_2,x_3,x_4)$ was made using the Design of Experiments (DoE) module of StatGraphics software, and a MSF-BR simulation program that we were developed [8]. The response surface methodology (RSM) was applied to approximate M_d and M_{hs}, and a quadratic polynomial function, having the following form, was fitted to obtain the RSM models:

$$y = A_0 + \sum_{i=1}^{4} A_i x_i + \sum_{i=1}^{4} A_{ii} x_i^2 + \sum_{j=2}^{4}\sum_{i=1}^{j-1} A_{ij} x_i x_j \tag{5}$$

The following correlations, given by StatGraphics software, were built by regression analysis using least-squares method:

$$M_d(x_1,x_2,x_3,x_4) = 429{,}117 + 6{,}1297(x_1 - 104) + 8{,}614.10^{-3}(x_2 - 2250) + 67{,}886.10^{-3}(x_3 - 2250) + 0{,}0789(x_4 - 2250) - 7{,}811.10^{-6}(x_3 - 2250)^2 - 6{,}304.10^{-6}(x_4 - 2250)^2 + 1{,}584.10^{-4}(x_1 - 104)(x_2 - 2250) + 0{,}994.10^{-3}(x_1 - 104)(x_3 - 2250) + 1{,}304.10^{-3}(x_1 - 104)(x_4 - 2250) + 0{,}3843.10^{-5}(x_2 - 2250)(x_3 - 2250) - 9{,}055.10^{-6}(x_3 - 2250)(x_4 - 2250). \tag{6}$$

$$M_{hs}(x_1,x_2,x_3,x_4) = 64{,}0637 + 0{,}746939(x_1 - 104) + 2{,}11274.10^{-3}(x_2 - 2250) + 0{,}01644186(x_3 - 2250) + 0{,}017294(x_4 - 2250) + 3{,}06135.10^{-5}(x_1 - 104)(x_2 - 2250) + 0{,}207.10^{-3}(x_1 - 104)(x_3 - 2250) + 0{,}2274.10^{-3}(x_1 - 104)(x_4 - 2250) + 0{,}085166.10^{-5}(x_2 - 2250)(x_3 - 2250) + 0{,}57344.10^{-6}(x_2 - 2250)(x_4 - 2250) + 0{,}64322.10^{-6}(x_3 - 2250)(x_4 - 2250). \tag{7}$$

Statistical analysis of the obtained models has been done using the Fisher test and the determination coefficient (R^2_{ajusted}). The probability of F-ratio of regression models for M_d and M_{hs} was respectively 0.0002 and 0.0001, which means that the models obtained are well precise for estimating these two parameters. R^2_{ajusted} for M_d and M_{hs} was respectively 0.9998 and 0.9999. These values reflects a very good fit between the simulation results and predicted results. Fig. 2 shows the adequacy graphs of M_d and M_{hs}. As can be seen here also, the predictions obtained using the above models are in good agreement with the simulation results, which confirms the good quality of the obtained models.

After obtaining the expressions of M_d and M_{hs}, the optimization problem can thus be defined as following

$$Min\ F = \begin{cases} f_1(x_1,x_2,x_3,x_4) = -\{[\,429{,}117 + 6{,}1297(x_1 - 104) + 8{,}614.10^{-3}(x_2 - 2250) + 67{,}886.10^{-3}(x_3 - 2250) + 0{,}0789(x_4 - 2250) - 7{,}811.10^{-6}(x_3 - 2250)^2 - 6{,}304.10^{-6}(x_4 - 2250)^2 + 1{,}584.10^{-4}(x_1 - 104)(x_2 - 2250) + 0{,}994.10^{-3}(x_1 - 104)(x_3 - 2250) + 1{,}304.10^{-3}(x_1 - 104)(x_4 - 2250) + 0{,}3843.10^{-5}(x_2 - 2250)(x_3 - 2250) - 9{,}055.10^{-6}(x_3 - 2250)(x_4 - 2250)]/[\,64{,}0637 + 0{,}746939(x_1 - 104) + 2{,}11274.10^{-3}(x_2 - 2250) + 0{,}01644186(x_3 - 2250) + 0{,}017294(x_4 - 2250) + 3{,}06135.10^{-5}(x_1 - 104)(x_2 - 2250) + 0{,}207.10^{-3}(x_1 - 104)(x_3 - 2250) + 0{,}2274.10^{-3}(x_1 - 104)(x_4 - 2250) + 0{,}085166.10^{-5}(x_2 - 2250)(x_3 - 2250) + 0{,}57344.10^{-6}(x_2 - 2250)(x_4 - 2250) + 0{,}64322.10^{-6}(x_3 - 2250)(x_4 - 2250)]\} \\ f_2(x_1,x_2,x_3,x_4) = \{x_2/[\,429{,}117 + 6{,}1297(x_1 - 104) + 8{,}614.10^{-3}(x_2 - 2250) + 67{,}886.10^{-3}(x_3 - 2250) + 0{,}0789(x_4 - 2250) - 7{,}811.10^{-6}(x_3 - 2250)^2 - 6{,}304.10^{-6}(x_4 - 2250)^2 + 1{,}584.10^{-4}(x_1 - 104)(x_2 - 2250) + 0{,}994.10^{-3}(x_1 - 104)(x_3 - 2250) + 1{,}304.10^{-3}(x_1 - 104)(x_4 - 2250) + 0{,}3843.10^{-5}(x_2 - 2250)(x_3 - 2250) - 9{,}055.10^{-6}(x_3 - 2250)(x_4 - 2250)]\} \\ f_3(x_1,x_2,x_3,x_4) = \{x_3/[\,429{,}117 + 6{,}1297(x_1 - 104) + 8{,}614.10^{-3}(x_2 - 2250) + 67{,}886.10^{-3}(x_3 - 2250) + 0{,}0789(x_4 - 2250) - 7{,}811.10^{-6}(x_3 - 2250)^2 - 6{,}304.10^{-6}(x_4 - 2250)^2 + 1{,}584.10^{-4}(x_1 - 104)(x_2 - 2250) + 0{,}994.10^{-3}(x_1 - 104)(x_3 - 2250) + 1{,}304.10^{-3}(x_1 - 104)(x_4 - 2250) + 0{,}3843.10^{-5}(x_2 - 2250)(x_3 - 2250) - 9{,}055.10^{-6}(x_3 - 2250)(x_4 - 2250)]\} \\ f_4(x_1,x_2,x_3,x_4) = \{x_4/[\,429{,}117 + 6{,}1297(x_1 - 104) + 8{,}614.10^{-3}(x_2 - 2250) + 67{,}886.10^{-3}(x_3 - 2250) + 0{,}0789(x_4 - 2250) - 7{,}811.10^{-6}(x_3 - 2250)^2 - 6{,}304.10^{-6}(x_4 - 2250)^2 + 1{,}584.10^{-4}(x_1 - 104)(x_2 - 2250) + 0{,}994.10^{-3}(x_1 - 104)(x_3 - 2250) + 1{,}304.10^{-3}(x_1 - 104)(x_4 - 2250) + 0{,}3843.10^{-5}(x_2 - 2250)(x_3 - 2250) - 9{,}055.10^{-6}(x_3 - 2250)(x_4 - 2250)]\} \end{cases}$$

$$93 \le x_1 \le 115$$
$$1500 \le x_2 \le 3000$$
$$1500 \le x_3 \le 3000$$
$$1500 \le x_4 \le 3000$$

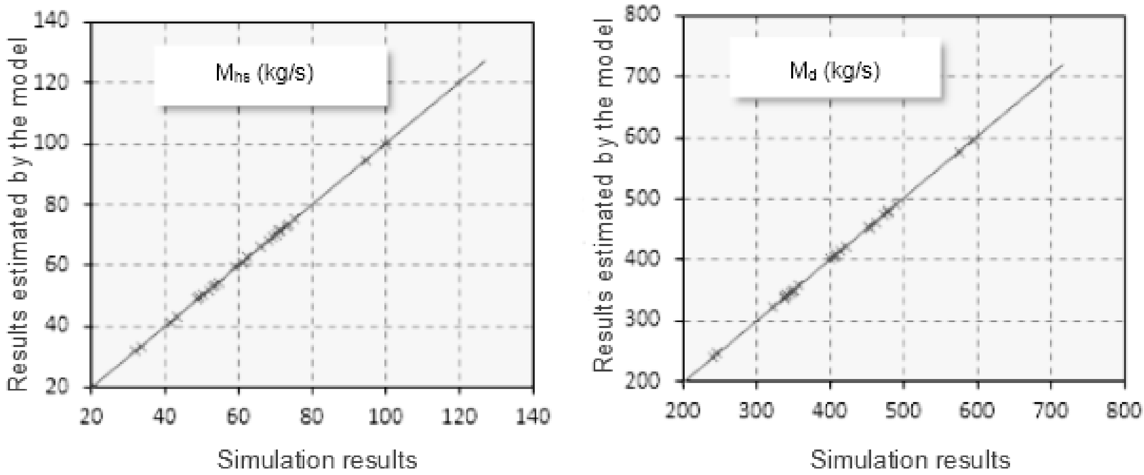

Figure 2. Comparison of simulation results and predicted model results

5. Resolution of the optimization problem

OP is a non-linear multi-objective optimization problem with inequality constraints. Genetic algorithms (GA) are well suited to solve multi-objective optimization problems. They have been used in many applications and their performances were tested in many studies [8,9-11], therefore, we chose a solver optimization tool of Matlab software (*gamultiobj*) using GA, for solving this problem. It finds a local Pareto front for multiple objective functions using the genetic algorithm [12]. For our problem (OP), the solver was used to obtain a Pareto front for four objective functions described in the MATLAB file.

The multi-objective GA function “gamultiobj” uses a controlled elitist genetic algorithm (a variant of NSGA-II) [12]. While the elitist GA always favors individuals with better fitness value (lower rank), the controlled elitist GA also favors individuals that tend to increase the diversity of the population even if they have a lower fitness value. In order to ensure the convergence to an optimal Pareto front, it is very important to maintain the diversity of population. This is done by controlling the elite members of the population as the algorithm progresses, by using the options, 'ParetoFraction' and 'DistanceFcn'. The Pareto fraction option limits the number of individuals on the Pareto front (elite members) and the distance function helps to maintain diversity on a front by favoring individuals that are relatively far away on the front**.**

The solver stops when the maximum number of generations is reached or the average change in the spread of the Pareto front over the 'StallGenLimit' generations is less than tolerance specified in options by the parameter TolFun.

In this study, the parameters used, by *gamultiobj* to solve the multi-objective optimization problem were fixed as following

- Population Size: 60
- Initial Population: Default
- Selection Function: Tournament
- Crossover operator: Scattered
- Tournament size: 2
- Crossover Fraction: 0.7
- Mutation Function: mutation_adapt_feasible
- Distance Measure Function: distance_crowding
- Pareto Front Population Fraction: 0.35

- Maximum Generations: Default : 800
- Time Limit: Infinite
- Stall Generations: 100
- Function Tolerance: 1×10^{-4}

6. Results and discussion

Table 2 shows the optimal values of the operating variables (Pareto optimal set) and the associated values of the objective function components (Pareto front), obtained during the resolution of the OP problem. The stopping of the algorithm was obtained after the satisfaction of the second criteria, while the number of generations has not exceeded 300.

The most important result of solving the optimization problem was the obtaining of large number of optimum operating points from which we can choose the ones that are most suitable for us. Indeed, if we want to favor thermal energy efficiency, we choose the points that gives us a great PR. However, if we want to favor electrical energy efficiency, we choose those that give us smaller specific flow rates (sM_{cw} + sM_R). If we want to reduce the specific consumption of antisacale chemicals, we choose the points with smaller sM_f.

Table 2. Optimal points and corresponding objective function components

Pareto optimal set				Objective functions			
x_1 : T_{hs} (°C)	x_2 : M_{cw} (kg/s)	x_3 : M_R (kg/s)	x_4 : M_f (kg/s)	$-f_1$: PR	f_2 : sM_{cw}	f_3 : sM_R	f_4 : sM_f
114.96	2368.9	2673.7	1610.2	6.9736	5.2353	5.9089	3.5585
114.92	2498.8	1565.0	2827.5	7.0051	5.2413	3.2826	5.9305
112.40	1646.2	1631.2	2886.5	6.9890	3.5373	3.5050	6.2024
114.24	2380.0	1565.3	2619.9	7.1357	5.2473	3.4512	5.7762
114.93	1741.5	1561.5	1603.2	8.0543	4.8904	4.3850	4.5021
114.70	2382.5	1564.2	1683.8	7.8801	6.4805	4.2546	4.5799
113.98	2411.5	1714.0	1609.3	7.7784	6.5139	4.6300	4.3471
112.28	2377.7	1611.8	2840.1	6.9333	5.1210	3.4715	6.1169
112.17	1811.3	2586.5	1608.6	7.0516	4.2753	6.1050	3.7968
114.57	1885.4	2128.0	2790.8	6.7012	3.7069	4.1838	5.4870
114.91	1688.3	2678.3	2761.4	6.4012	3.1113	4.9356	5.0887
114.63	1607.6	2014.8	2836.2	6.7919	3.1997	4.0101	5.6451
114.41	2499.8	1565.9	2131.1	7.4764	6.0890	3.8143	5.1908
114.19	1990.9	1785.5	2624.5	7.0119	4.2532	3.8144	5.6070
111.85	1611.7	1807.8	2864.8	6.8746	3.4115	3.8266	6.0640
114.70	2416.1	1782.7	2460.3	7.0798	5.2560	3.8781	5.3521
111.57	1737.4	2562.0	1904.8	6.8837	3.9186	5.7786	4.2961
114.29	2514.2	1945.2	1613.9	7.5501	6.4008	4.9522	4.1087
114.28	2560.4	1577.7	1614.1	7.9150	7.0901	4.3687	4.4697
114.99	1606.7	2574.7	2728.3	6.4927	3.0133	4.8288	5.1168
114.23	2470.3	1576.9	1605.5	7.9281	6.8737	4.3877	4.4674

Table 3 gives the values of the operating parameters of the installation and the corresponding components of the objective function for 4 cases

- Case 1 corresponds to the operating points where f_1 is minimum (PR is maximum).
- Case 2 corresponds to the operating points where f_2 is minimum.
- Case 3 corresponds to the operating points where f_3 is minimum.
- Case 4 corresponds to the operating points where f_4 is minimum.

The improvement (in %) obtained between these operating points, and that of the actual state of the studied installation is shown in Figure 3 and Table 3. We observe that the improvement is significant, indeed, the improvement on the thermal performance ratio is equal to 14.08 % in case 1, on the specific cooling water flow rate is equal to 100.80% in case 2, on the specific recirculating brine flow rate is equal to 81.98% in case 3, and on the specific feed flow rate is equal to 70.91% in case 4. Therefore, run the installation in one of these cases certainly reduces the operating cost of the installation and therefore reduce the cost of fresh water produced. Also it can be noted that for the four cases the value of T_{hs} is close to 115°C which corresponds to the upper limit of this variable.

Table 3. Comparison between the current operational state of the installation and states corresponding to the case 1, 2, 3 and 4

	T_{hs} (°C)	M_{cw} (kg/s)	M_R (kg/s)	M_f (kg/s)	PR	sM_{cw}	sM_R	sM_f
Current state	97	1569.6	1755.5	1577.7	6.9228	6.0508	5.9737	6.0821
Case 1	114.93	1741.5	1561.5	1603.2	8.0543	4.8904	4.3850	4.5021
Improvement (%)	----	----	----	----	14.05	23.72	36.23	35.09
Case 2	114.99	1606.7	2574.7	2728.3	6.4927	3.0133	4.8288	5.1168
Improvement (%)	----	----	----	----	-6.62	100.80	23.71	18.86
Case 3	114.92	2498.8	1565.0	2827.5	7.0051	5.2413	3.2826	5.9305
Improvement (%)	----	----	----	----	1.83	15.44	81,98	2.55
Case 4	114.96	2368.9	2673.7	1610.2	6.9736	5.2353	5.9089	3.5585
Improvement (%)	----	----	----	----	0.73	15.57	1.09	70.91

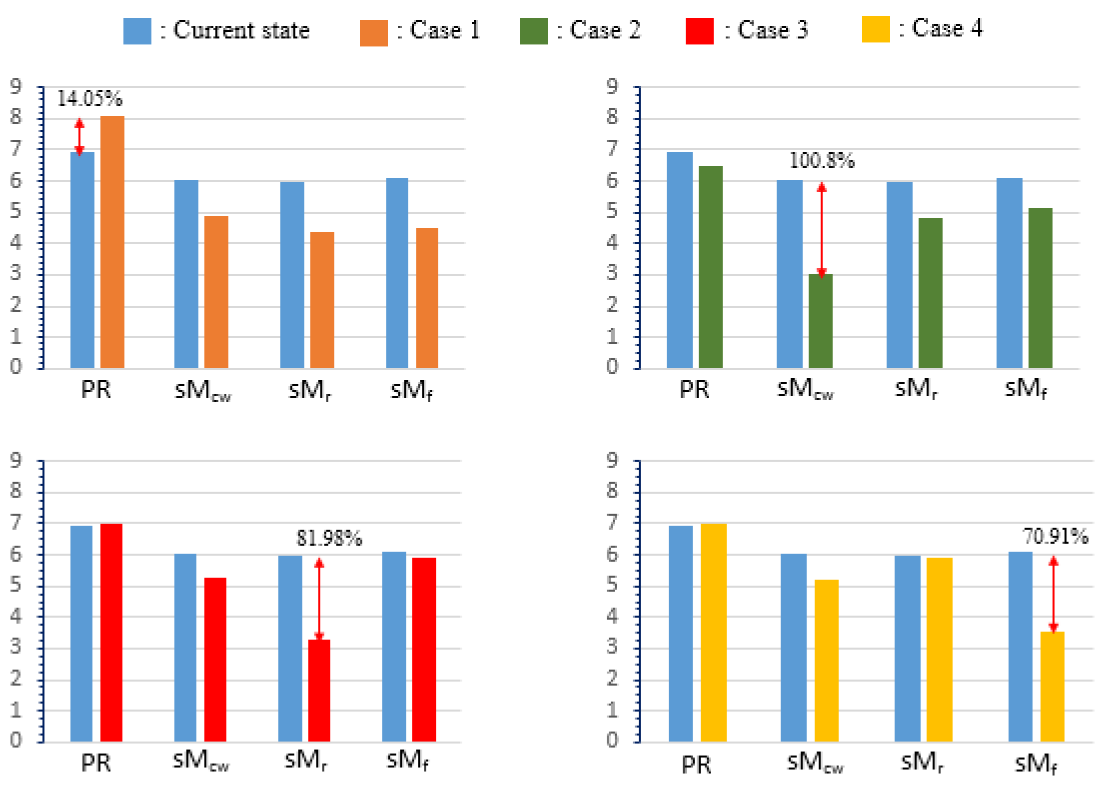

Figure 3. Comparison between the current operational state of the installation and states corresponding to the case 1, 2, 3 and 4

6. Conclusion

In this study, an optimization of operating parameters of a large-scale MSF-BR desalting plant was done. The plant includes 13 flashing stages in heat recovery section and 3 flashing stages in heat rejection section.

The objective functions of the optimization problem were selected among the plant performance indicators, which controls specific consumption of steam, electricity, and chemicals. Thus, during this optimization, the thermal performance ratio (PR) was maximized while the specific cooling water flow rate (sM_{cw}), the specific recirculating brine flow rate (sM_r), and the specific feed flow rate (sM_f) were minimized.

The optimization problem has been solved using the multi-objective solver (*gamultiobj*) available in the MATLAB optimization toolbox. This solver uses genetic algorithms for finding the Pareto-optimal solutions. The optimization approach leads to obtaining a large set of Pareto optimal solutions, which defining various combinations of the optimal operating parameters of a MSF-BR desalination plant. The optimization results reveal that a significant improvement of the performance indicators can be obtained if we use the optimal operating points given by solving the optimization problem.

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