



Thermal-economic optimization of shell and tube heat exchanger using a new multi-objective optimization method

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ABSTRACT

Many studies have been performed by researchers about Shell and Tube Heat Exchanger but the Multi-Objective Big Bang-Big Crunch Algorithm (MOBBA) technique has never been used in such studies. This study presents application of thermal-economic multi-objective optimization of shell and tube heat exchanger using MOBBA. For an optimal design of a shell and tube heat exchanger, it was first modelled thermally using e-NTU method while Bell-Delaware procedure was applied to estimate its shell side heat transfer coefficient and pressure drop. The MOBBA method was applied to obtain the maximum effectiveness (heat recovery) and the minimum total cost as two objective functions. The results of the optimal designs are a set of multiple optimum solutions, called 'Pareto optimal solutions'. In order to show the accuracy of the algorithm, a comparison is made with the Non-dominated Sorting Genetic Algorithm (NSGA-II) and MOBBA which are developed for the same problem.

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1. Introduction

Shell and tube heat exchangers are probably the most common type of heat exchangers applicable for a wide range of operating temperatures and pressures. Shell and tube heat exchangers are widely used in refrigerating, power generating, heating and air conditioning, chemical processes, manufacturing and medical applications.

A typical shell and tube heat exchanger is shown in [1, 2]. This widespread use can be justified by its versatility, robustness and reliability. The design of Shell and Tube Heat Exchangers (STHEs) involves a large number of geometric and operating variables as a part of the search for an exchanger geometry that meets the heat duty requirement and a given set of

design constrains. Usually a reference geometric configuration of the equipment is chosen at first and an allowable pressure drop value is fixed. Then, the values of the design variables are defined based on the design specifications and the assumptions of several mechanical and thermodynamic parameters in order to have a satisfactory heat transfer coefficient leading to a suitable utilization of the heat exchange surface. The designer's choices are then verified based on iterative procedures involving many trials until a reasonable design is obtained which meets the design specifications with a satisfying compromise between pressure drops and thermal exchange performances [1, 2].

Designing the heat exchangers is a complex procedure and it requires a good knowledge of

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thermodynamics, fluid dynamics, cost estimation and optimization. The objectives involved in the design optimization of heat exchangers are thermodynamic (i.e. maximum efficiency) and economic (i.e. minimum cost). The conventional design approach for heat exchangers involves rating a large number of different exchanger geometries to identify those designs that satisfy a given heat duty and a set of geometric and operational constraints. This approach is time-consuming, and does not guarantee an optimal solution. [3]

2. Literature Review

Several studies are presented to propose optimization of shell and tube heat exchanger. Min Zhao and Yanzhong Li used an effective layer pattern optimization model for multi-stream plate-fin heat exchanger using genetic algorithm. In this study, an effective layer pattern optimization model using Genetic Algorithm (GA) was developed in detail [4]. Suxin Qian et al. presented applicability of entransy dissipation based thermal resistance for the design optimization of two-phase heat exchangers. In this study, the evaluation of two-phase entransy was achieved by optimizing one tube-fin heat exchanger and one micro channel heat exchanger based on a validated heat exchanger modeling tool [5]. Khaled Saleh et al. applied approximation assisted optimization of headers for a new generation of air-cooled heat exchangers. In this study an online multi-objective approximation assisted optimization approach was used to design optimum headers for compact air-cooled heat exchangers [6]. Amin Hadidi and Ali Nazari used the design and economic optimization of shell-and-tube heat exchangers using Biogeography-Based Optimization (BBO) algorithm. In this research, a new shell and tube heat exchanger optimization design approach was developed based on biogeography-based optimization (BBO) algorithm. The BBO algorithm has some good features in reaching the global minimum in comparison with other evolutionary algorithms [7]. SalimFettaka et al. developed the design of shell-and-tube heat exchangers using multi-objective optimization. In this study, a multi-objective optimization of the heat transfer area and pumping power of a shell-and-tube heat exchanger was presented to provide the designer with multiple Pareto-optimal solutions which captured the trade-off between the two objectives [8]. Sreepathi and G.P. Rangaiah applied an improved heat exchanger network retrofitting using exchanger reassignment strategies and multi-objective optimization. In this study, several ERS (exchanger reassignment strategies) for HEN retrofitting were proposed and tested by performing single objective optimization

on retrofit problems using IDE (integrated differential evolution) [9]. Viviani C. Onishiet al. developed a mathematical programming model for heat exchanger design through optimization of partial objectives. Mathematical programming can be used for the optimal design of Shell-and-Tube Heat Exchangers (STHEs). This study proposed a Mixed Integer Non-Linear Programming (MINLP) model for the design of STHEs, following rigorously the standards of the Tubular Exchanger Manufacturers Association (TEMA). Bell-Delaware Method was used for the shell-side calculations [10]. Jiang feng Guo et al. used multi-objective optimization of heat exchanger based on entransy dissipation theory in an irreversible Brayton cycle system. In this study a multi-objective optimization of the main heat exchanger in a regenerative Brayton cycle system was carried out based on entransy dissipation. The best trade-off between the entransy dissipation numbers caused by heat transfer and fluid friction is achieved in the Pareto optimal solutions and a decrease in the entransy dissipation related to heat transfer inevitably leads to an increase in the entransy dissipation due to fluid friction, and vice versa. The entransy dissipation plays a decisive role in the network output due to heat transfer rather than due to fluid friction [11]. R. Venkata Rao and Vivek Patel et al. presented multi-objective optimization of heat exchangers using a modified teaching-learning-based optimization algorithm. In this study, a modified version of the TLBO algorithm was introduced and applied for the multi-objective optimization of heat exchangers. The plate-fin heat exchanger and the shell and tube heat exchanger were considered for the optimization [12]. Ming Pan et al. used optimization for the retrofit of large scale heat exchanger networks with different intensified heat transfer techniques. In this study, an optimization method was developed for dealing with the retrofit of large scale HENs in which the location of intensified heat transfer within the network and its degree of intensification were identified systematically, given the objective function and design constraints, including the topological limitation in the existing heat recovery systems[13]. Juan I. Manassaldi et al. presented optimization mathematical model for the detailed design of air cooled heat exchangers. This study presents a disjunctive mathematical model for the optimal design of air cooled heat exchangers. The model involves seven discrete decisions which are related to the selection of the type of the finned tube, the number of tube rows, the number of tube per row, the number of passes, the fins per unit length, the mean fin thickness and the type of the flow regime. Each discrete decision is modeled using disjunctions, boolean variables and logical propositions. The main continuous decisions are fan diameter, bundle width,

tube length, pressure drops and velocities in both sides of the ACHE, heat transfer area and fan power consumption[14]. Vivek Patel and VimalSavsani presented optimization of a plate-fin heat exchanger design through an improved Multi-Objective Teaching-Learning Based Optimization (MO-ITLBO) algorithm. In this study, the Multi-Objective Improved Teaching-Learning-Based Optimization (MO-ITLBO) algorithm was introduced and applied for the multi-objective optimization of plate-fin heat exchangers[15]. Costa and Queiroz developed design optimization of shell-and-tube heat exchangers [16]. Caputo et al. presented heat exchanger design based on the economic optimization [17]. Fesanahary et al. applied a harmony search algorithm to design optimization of shell and tube heat exchangers [18]. Hilbert et al. developed parallel genetic algorithms to shape optimization of a heat exchanger [19]. Sanaye and Hajabdollahi used multi-objective optimization of shell and tube heat exchangers [20]. Ponce-Ortega et al. used the genetic algorithms for the optimal design of shell-and-tube heat exchangers [21]. Jie Yang et al. developed optimization of shell-and-tube heat exchangers using a general design approach motivated by constructal theory [22]. Daniël Walraven et al. used optimum configuration of shell-and-tube heat exchangers in low-temperature organic Rankine cycles [23]. Jie Yang et al. developed optimization of shell-and-tube heat exchangers conforming to TEMA standards with the designs motivated by constructal theory [24]. Mohsen Amini and Majid Bazargan used two-objective optimization in shell-and-tube heat exchangers using genetic algorithm [25]. Literature review also indicates that BBA algorithm has never been used for such a study.

2. Mathematical Model for Optimization of Shell and Tube Heat Exchanger Mathematical model

Based on the work of Sanaye and Hajabdollahi [20], effectiveness of the standards of the Tubular Exchanger Manufacturers Association (TEMA) E-type Shell and Tube Heat Exchanger (STHE) is given as the following[20]:

$$\varepsilon = 2 \left\{ \frac{1 - \exp \left[-NTU \sqrt{1 + C^2} \right]}{1 + C + \sqrt{1 + C^2}} \right\}^{-1} \quad (1)$$

Where the number of transfer units (NTU) and the heat capacity ratio (C) are defined as follows [20]:

$$NTU = \frac{UA_t}{C_{\min}} = \frac{UA_t}{(\dot{m}C_p)_{\min}} \quad (2)$$

$$C = \frac{C_{\min}}{C_{\max}} \quad (3)$$

Where A_t is the total tube outside heat transfer surface area and U_o is the overall heat transfer coefficient which is computed by the following equation [20]:

$$A_t = \pi L d_o N_t \quad (4)$$

Where L , N_t , d_i , d_o , $R_{i,f}$, $R_{o,f}$, and k_w are the tube length, tube number, tube inside and outside diameter, tube and shell side fouling resistances and thermal conductivity of tube wall respectively.

$$1/U_o = 1/h_o + R_{o,f} + d_o \ln(d_o/d_i) / 2k_w + R_{i,f} + 1/h_i(d_o/d_i) \quad (5)$$

The tube side heat transfer coefficient is estimated by the following equation [20]:

$$h_i = (k_t/d_i) 0.024 Re_t^{0.8} Pr_t^{0.4} \quad (6)$$

$2500 < Re_t < 1.24 * 10^5$

Where k_t and Pr_t are the tube side fluid thermal conductivity and Prandtl number respectively. Also Re_t is the tube flow Reynolds number which is defined as follows [20]:

$$Re_t = \frac{m_t d_i}{\mu A_{o,t}} \quad (7)$$

Where m_t is the mass flow rate and $A_{o,t}$ is the tube side flow cross section area per pass estimated as [20]:

$$A_{o,t} = 0.25\pi d_i^2 N_t / n_p \quad (8)$$

And n_p is the number of tube passes. Furthermore, the tube side pressure drop is also estimated by the following formula:

$$\Delta p_t = G^2 / 2\rho \left[(1 - \sigma^2 + K_c) + 2(\rho_i / \rho_o - 1) + 4f_t L / d_i (1/\rho)_m - (1 - \sigma^2 - K_e) \rho_i / \rho_o \right] \quad (9)$$

Where ΔP_t includes the pressure drop due to the flow contraction, acceleration, friction, and expansion, four terms in Eq. (9). K_c and K_e are the tube entrance and exit pressure loss coefficients. Furthermore f_t is the tube side friction factor estimated as the following [20]:

$$f_t = 0.000128 + 0.1143(Re_t)^{-0.311} \quad (10)$$

The shell diameter is estimated by the following equation:

$$D_s = 0.637 p_t \sqrt{(\pi N_t) CL / CTP} \quad (11)$$

The shell side Reynolds number is as follows:

$$Re = \frac{G_s d_o}{\mu} = \frac{u_s \rho d_o}{\mu} \quad (12)$$

Where p_t is the tube pitch and CL is the tube layout constant that has a unit value for 45 and 90 tube arrangements and 0.87 for 30 and 60 tube arrangements. Also, CTP is the tube count constant which is 0.93, 0.9, and 0.85 for the single pass, two passes and three passes of tubes, respectively.

Bell-Delaware method is used in this study to compute the shell side heat transfer coefficient and pressure drop. For more information, readers are referred to ref. [20].

3. Entropy Generation Number

The irreversibility losses in the heat exchanger are evaluated in terms of entropy generation. The entropy generation rate caused by the finite temperature difference $\dot{S}_{gen}, \Delta T$ can be written as follows [26]:

$$\dot{S}_{gen}, \Delta T = \int_i^o \left(\frac{\dot{m} Cp dT}{T} \right)_{1,2} = \quad (13)$$

$$(\dot{m} Cp)_1 \ln \left(\frac{T_{s,o}}{T_{s,i}} \right) + (\dot{m} Cp)_2 \ln \left(\frac{T_{t,o}}{T_{t,i}} \right)$$

For an incompressible fluid under non-adiabatic condition the entropy generation rate $\dot{S}_{gen}, \Delta P$ caused by fluid friction is expressed as follows [26]:

$$\dot{S}_{gen}, \Delta P = \left[\dot{m} \frac{\Delta P}{\rho} \frac{\ln \left(\frac{T^o}{T^i} \right)}{T^o - T^i} \right]_{1,2} = \quad (14)$$

$$\dot{m}_1 \frac{\Delta P}{\rho_1} \frac{\ln \left(\frac{T_{s,o}}{T_{s,i}} \right)}{T_{s,o} - T_{s,i}} + \dot{m}_2 \frac{\Delta P}{\rho_2} \frac{\ln \left(\frac{T_{t,o}}{T_{t,i}} \right)}{T_{t,o} - T_{t,i}}$$

The total entropy generation rate in heat exchanger can be written as follows [26]:

$$\dot{S}_{gen} = \dot{S}_{gen}, \Delta P + \dot{S}_{gen}, \Delta T = \dot{m}_1 \frac{\Delta P}{\rho_1} \frac{\ln \left(\frac{T_{s,o}}{T_{s,i}} \right)}{T_{s,o} - T_{s,i}} + \quad (15)$$

$$\dot{m}_2 \frac{\Delta P}{\rho_2} \frac{\ln \left(\frac{T_{t,o}}{T_{t,i}} \right)}{T_{t,o} - T_{t,i}} + (\dot{m} Cp)_1 \ln \left(\frac{T_{s,o}}{T_{s,i}} \right) + (\dot{m} Cp)_2 \ln \left(\frac{T_{t,o}}{T_{t,i}} \right)$$

When the heat capacity rate of the hot fluid is larger than that of the cold fluid, the outlet temperature of both fluids can be calculated as follows [20]:

$$T_{s,o} = T_{s,i} - \varepsilon \frac{C_{\min}}{C_s} (T_{s,i} - T_{t,i}) \quad (16)$$

$$T_{t,o} = T_{t,i} + \varepsilon \frac{C_{\min}}{C_t} (T_{s,i} - T_{t,i}) \quad (17)$$

4. Multi-Objective Optimization Problems

Many optimization problems can be presented by the following general mathematical model [27]:

$$\text{Max. /Min. } F(x) \quad x \in X \quad (18)$$

$$F: X \rightarrow R \quad (19)$$

In which $f(x)$ is the objective function, x is the decision variables vector, X is the decision variables space, and R is the set of real numbers.

Figure (1-a) shows a schematic of transferring data from a two dimensional decision variable space to a decision space in single objective problems. In multi-objective optimization problems, optimizing a vector of objectives is considered instead of satisfying a single objective.

Generally, in mathematical form, multi-objective optimization problems can be defined as follows [27]:

$$\text{Max. /Min } f(x) = (f_1(x), f_2(x) \dots f_m(x)) \quad (20)$$

$$x \in X$$

$$F: X \rightarrow R^m, m \in M \quad (21)$$

Where m denotes the set of natural numbers and N denotes the number of objectives. There are techniques such as the weighting method and ε -constraint method which transfer multi-objective problems to a single-objective one using different combinations of a weighting vector and constraints. Thus, each optimal solution can be assigned to a specific combination of weighting vector and constraint. Hence, in each run of the algorithm, a single point (solution) can be achieved. However, multi-objective evolutionary algorithms are capable of finding almost all candidate solutions (Pareto) in a single run.

Figure (1-b) presents a schematic of transferring data from two dimensional decision variables space to the decision space in a two-objective problem.

As it is shown, each set of decision variables has been related to a couple of objectives. Note that none of the solutions dominates the others. In other words, if all the objective values of a solution dominate the corresponding values of another solution, the former will be a dominated solution and the latter will be removed. Otherwise, both solutions will be located in the non-dominated set.

The dominated and non-dominated relations between objectives values in a bi-objective problem are shown in Fig.2. Both objectives are minimized. In this figure, the solutions labeled by 1 or 2 have non-dominated conditions individually. We should note that the set labeled 1 dominates the set labeled 2. In the optimization procedure, the best set of non-dominated solutions is called Pareto-front. Thus, there are two Pareto in Figure (2), and the one which is labeled 1 is the Pareto-front. [27]

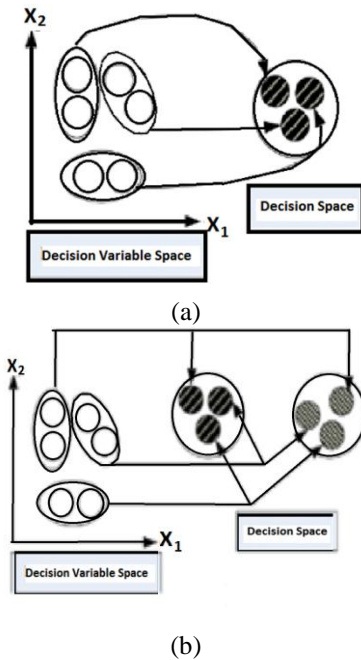


Fig. 1 The schematic of decision and decision variable spaces in: (a) single-objective and (b) multi-objective problems.

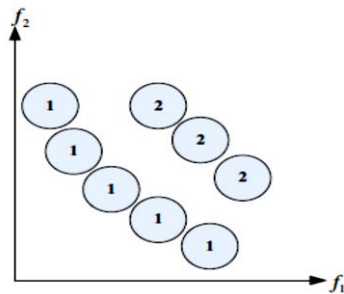


Fig.2 The schematic of dominated and non-dominated conditions of solutions in a projective problem.

The analogy of Big Bang - Big Crunch Algorithm (BB-BCA) with evolutionary algorithms makes it evident that using a Pareto ranking scheme [28] could be the straightforward way to extend the approach to handle the multi-objective optimization problems. The historical record of the best solutions found by a particle (i.e., an individual) could be used to store non-dominated solutions generated in the past (this would be similar to the notion of elitism used in evolutionary multi-objective optimization). The use of global attraction mechanisms combined with a historical archive of previously found non-dominated vectors would motivate convergence toward globally non-dominated solutions.

5. Big Bang-Big Crunch Algorithm (BBA)

In the BB-BC algorithm proposed by Erol and Eksin[29], the initial big-bang is identical to the first step of the other evolutionary methods in that an initial population of candidate solutions is randomly generated over the entire search space. Erol and

Eksin compared this random nature of the Big Bang to the energy dissipation or the transformation from an ordered state (a convergent solution) to a chaotic state (generation of new set of candidate solutions). In the Big Crunch phase following the Big Bang, a contraction operation is applied to randomly distributed candidate solutions. The contraction operator takes the current positions (represented by the values of the design variables) of each candidate solution in the population and its corresponding penalized fitness function value to compute a center of mass. The center of mass is the weighted average of the candidate solution positions where the weight associated with the position of each candidate solution is the inverse of the corresponding penalized fitness function. The averaging is done with respect to the inverse of the penalized fitness function values. The center of mass \vec{X}_{cm} is computed as the following [29]:

$$\vec{X}_{cm} = \frac{\sum_{k=1}^{NC} \frac{\vec{X}_k}{F_k}}{\sum_{k=1}^{NC} \frac{1}{F_k}} \quad (22)$$

Where \vec{X}_k is the position of candidate k in an n-dimensional searchspace, F_k is the penalized fitness function value of candidate k, and NC is the candidate population size. New positions \vec{X}_k^{new} of the candidate solutions for the next iteration of the Big Bang are obtained using the following equation [29]:

$$\vec{X}_k^{new} = \vec{X}_{cm} + \vec{\sigma} \quad (23)$$

Where $\vec{\sigma}$ is the standard deviation of the normal distribution. In the BB-BC algorithm, the standard deviation $\vec{\sigma}$ is related to a subset of search space and is obtained by the following equation [29]:

$$\vec{\sigma} = \frac{r \alpha_1 (\vec{X}_{max} - \vec{X}_{min})}{n_{cycle}} \quad (24)$$

Where r is a random number from a standard normal distribution, α_1 is a parameter limiting the size of the search space, \vec{X}_{max} and \vec{X}_{min} are the upper and lower limits of the values of the design variables respectively, and n_{cycle} is the number of Big Bang iterations.

In order to improve the computational efficiency of BB-BC algorithm, Kaveh and Talatahari use the social behaviour of bird flocking and fish schooling model in particle swarm optimization. The swarm's movement is directed by both their own experience and the population's experience. For every iteration, a particle moves towards a direction computed from the local best solution and the global best solution. This concept is used in this study where the BB-BC algorithm not only utilizes the center of mass but also employs the global best solution to generate the new solution.

A modified version of Eq. (23) is given as follows [29]:

$$\begin{aligned} \vec{X}_k^{new} &= \alpha_2 \vec{X}_{cm} \\ &+ (1 - \alpha_2) [\alpha_3 \vec{X}_l^{best} \\ &+ (1 - \alpha_3) \vec{X}_g^{best}] \\ &+ \frac{r \alpha_1 (\vec{X}_{max} - \vec{X}_{min})}{n_{cycle}} \end{aligned} \quad (25)$$

Where α_2 , α_3 are the controlling parameters, \vec{X}_l^{best} is the local best solution, and \vec{X}_g^{best} is the global best solution. Since normally distributed numbers can exceed ± 1 , it is necessary to limit candidate positions to the prescribed search space boundaries. As a result of this contraction, there is an accumulation of candidate solutions at the search space boundaries.

In Eq. (25) α_1 , α_2 and α_3 are the adjustable parameters that control the influence of the local and the global best solutions on the new positions of candidate solutions.

In addition, the BB-BC algorithm employs a multiphase search. In a two-phase search, the BB-BC algorithm is initially applied to the entire search space. After the convergence of Phase I, the Phase II search starts in a reduced search around \vec{X}_g^{best} from Phase I. The search space is reduced to 20% of the original search space [30].

6. Economic Modelling

The total cost of the STHE heat exchanger is given by the following [20]:

$$C_{tot} = C_{op} + C_{in} \quad (26)$$

Where C_{in} and C_{op} are the total investment cost and the operating cost of the heat exchanger respectively and are defined as follows [20]:

$$co = pk_{el}\tau \quad (27)$$

$$C_{in} = 8500 + 409A^{0.85} \quad (28)$$

$$p = (\dot{m}_t \Delta p_t / \rho_t + \dot{m}_s \Delta p_s / \rho_s) (1/\eta)$$

Where n_y is the equipment life in year, i is the annual discount rate and k is the depreciation time in year. Also, ΔP and m are the pressure drop and the mass flow rate of the fluid. Cop is the annual operating cost and it is calculated as follows:

$$C_{op} = \sum_{k=1}^{n_y} co / (1 + i)^k \quad (29)$$

Where k_{el} , τ and n_p are the electricity unit cost, the operation hours of the heat exchanger per year and the pump efficiency respectively. The detailed calculation of different parameters of the above mentioned equations is given in Refs. [20, 26].

7. Case Study

The analysis of the case study has been performed by Sanaye et al. [20] using NSGA-II approach according to the literature [2]. The original design specifications, shown in Table (1), are fed as inputs into the MOBBA algorithm.

In Figure (3), the optimal heat exchanger architectures obtained by MOBBA are compared with those of Sanaye et al. [20] using the NSGA-II approach and also with the original design solution given by Shah et al. [2].

The application example of STHE was also analysed to ensure the capability of MOBBA which was earlier analysed using NSGA-II by Sanaye and Hajabdollahi [20]. With the help of fresh water, the oil cooler STHE used to lower the temperature of the oil was designed and optimized for providing the maximum effectiveness and the minimum total cost. The high temperature of oil with mass flow rate of 8.1 kg/s was poured into the shell side of STHE at a temperature of 78.3 °C. Also, the fresh water with mass flow rate of 12.5 kg/s at a temperature of 30 °C was poured into the tube side of STHE. The thermo physical properties of both the fluids were taken from Ref. [20].

The following inequality constraints which are bound by lower and upper limits of the design variables are considered in the present study and three different tube arrangements (30°, 45° and 90°) are also considered for the optimization.

$$0.0112 \leq di \leq 0.0153$$

$$1.25 \leq pt/do \leq 2$$

$$3 \leq L \leq 8$$

$$100 \leq Nt \leq 600$$

$$0.19 \leq bc/Ds \leq 0.32$$

$$0.2 \leq bs/Ds \leq 1.4$$

$$3 \leq L/Ds \leq 12$$

In this study, the following assumptions were made:

- Price of electricity (k_{el}) : 0.15 \$/kWh,
- Equipment life period (n_y) : 10 years
- Annual discount rate (i) : 10%,
- Hours of operation per year (s) : 7500 h/yr
- Pump efficiency (η) : 0.6

Table1. The process input and physical properties for different case studies"

| Properties | Pr | K(W/m ² .K) | Cp(j/kg.K) | μ (Pa.s) | R_f |
|------------|------|------------------------|------------|--------------|----------|
| Shell side | 966 | 0.14 | 2115 | 0.0643 | 0.00015 |
| Tube side | 4.77 | 0.634 | 4120 | 0.000695 | 0.000074 |

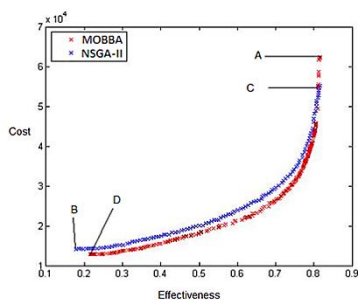


Fig.3 The optimized point's distribution in pareto by using MOBBA

8. Distance Criterion

The distance criterion measures (d) cover and give distribution to the proposed space. In this study, the distance criterion is used to compare the results of two algorithms, MOBBA and NSGA-II. The result is discussed in section 9.

$$d = \sqrt{1/n - 1 \sum_{i=1}^n (\bar{d} - d_i)^2} \tag{30}$$

$$d_i = \min_j \left\{ \sum_{m=1}^M |f_m^i(\bar{x}) - f_m^j(\bar{x})| \right\} \tag{31}$$

$i, j = 1, \dots, n$

Also, using d_i , we can find the minimum point distance of the diagram based on the ideal point using such criterion [20].

9. Optimization Results

The numbers of iterations for finding maxima or minima, in the search space are almost 104 and the number of populations and repositories are 100. The results are shown in figure (4) via the Pareto diagram. The figure demonstrates clearly the presented differences between both objective functions.

Increasing heat transfer in the heat exchanger, the total cost would increase. So, we use multi- objective optimization method for shell-tube heat exchanger to decrease the cost. Figure (6) shows the minimum amounts of total cost with the least effectiveness. Here, the MOBBA algorithm results are compared with the results of the NSGA- II algorithm previously proposed by Mr. Sanaye in 2010 [20].

We use distance criterion for comparing the results of two algorithms, MOBBA and NSGA-II, which this scale is 0.3919 for the NSGA-II algorithm and 0.3112 for the MOBBA algorithm. These amounts indicate that the point achieved by the MOBBA algorithm is closer to the ideal point rather than the point achieved by the NSGA-II algorithm. Figure (4) shows a better performance of the MOBBA algorithm compared to the NSAG- II algorithm.

For both algorithms in the figure (3), A and C points are happened when optimization is done as a single objective and so our objective functions are

maximization of the effectiveness. For B and D points, our objective functions are minimization of the total cost. Figures (5) and (6) are related to the maximum effectiveness and minimum total cost, respectively. It is obvious that for the total cost, the results in the MOBBA algorithm are optimized to 7.36 % and so for Q maximum, the MOBBA algorithm has better results than the NSGA-II.

10. External Temperatures

According to the equations (16) and (17) the relations for external temperatures of heat exchanger and the amounts of these temperatures are obtained based on the limitation of the total cost, effectiveness and decision variables in figure (3) for both algorithms in the figures (8) to (10).

These figures emphasize the problem that there is an external temperature in the tube for an external temperature in the shell with the optimized amounts of decision variables. The maximum amounts of effectiveness in (16) and (17) equations are accompanied with the minimum amounts for external temperature of the shell, and the maximum external temperature of the tube.

Also, the optimized amount of the external temperature in the tube is 63.85 for the MOBBA algorithm and for the external temperature of the shell is 44.440C

11. Entropy Balance

Figure (11) and figure (12) show the entropy amounts based on the effectiveness and also show the total cost for highlighted points in figure (3).

Figure (11) shows the entropy amount based on the output heat. More specifically, it shows that the amount of system entropy increases with increasing the output.

Also, figure (12) shows incurred cost increased with increasing the output. For the amount of the best optimized point, which is obtained by pareto diagram in figure (3) for the MOBBA algorithm, the amount of effectiveness is 0.7051 and the cost is 28184 \$ and the amount of produce entropy cost is 29287.

12. Conclusion

Designing the heat exchanger can be a complicated task. Thus, the advanced optimization methods are useful for identifying the best and cheapest heat exchanger for a specific duty. In this study, the shell and tube heat exchanger design and the multi-objective optimization are performed with the MOBBA algorithm. The results are compared with those of Sanaye paper [20]. The MOBBA algorithm is a useful method for the shell and tube heat exchanger design and optimization. These results are demonstrated in similar conditions for two-objective functions (effectiveness and total cost)

and indicate that the MOBBA is a better and more effective method than the NSGA-II algorithm. The algorithm proposed here can help the manufacturer and engineers to optimize heat exchangers in engineering applications.

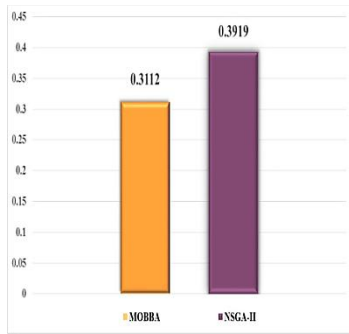


Fig. 4 The related results to D criterion for the MOBBA & NSGA-II.

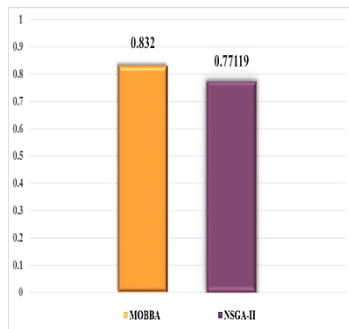


Fig. 5 The comparison of the maximum effectiveness for the MOBBA& NSGA-II[8].

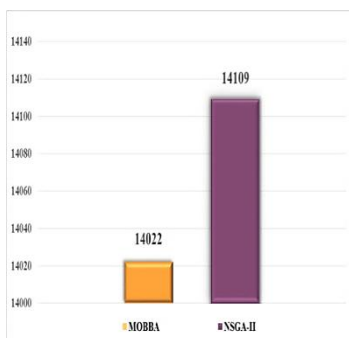


Fig. 6 The comparison of the least total cost for MOBBA& NSGA-II [8].

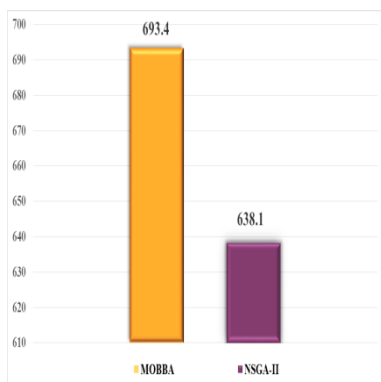


Fig. 7 The comparison of the maximum heat transfer for the MOBBA& NSGA-II [8].

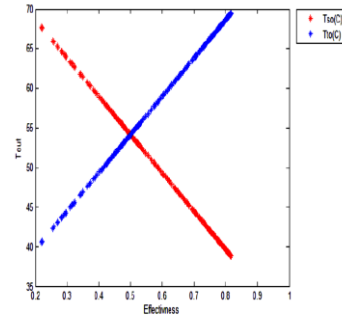


Fig. 8 The external temperature based on effectiveness for the MOBBA& NSGA-II [8].

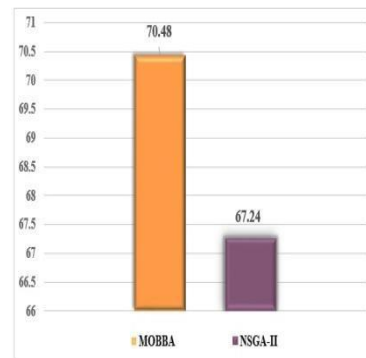


Fig. 9 The comparison of the maximum tube external temperature for the MOBBA& NSGA-II [8].

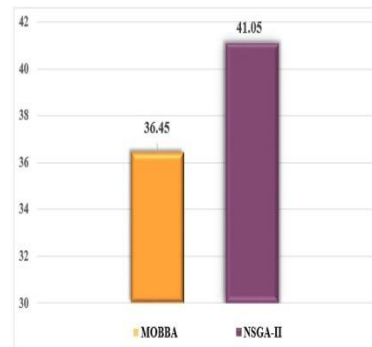


Fig. 10 The comparison of the least shell external temperature for the MOBBA & NSGA-II [8].

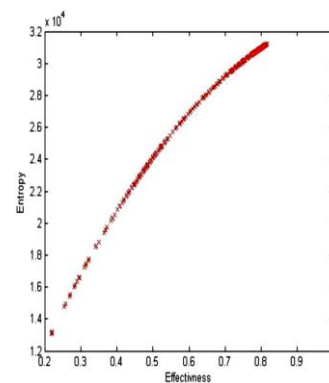


Fig. 11 The entropy balance based on effectiveness efficiency for the MOBBA.

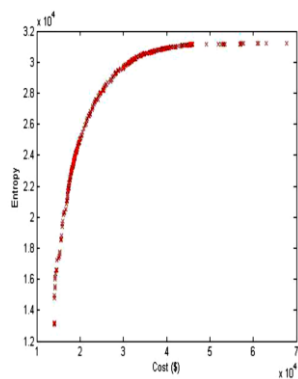


Fig. 12 The entropy balance based on total cost for the MOBBA.

| | | |
|----------|---|----------------------|
| σ | coefficient | |
| σ | ratio of minimum free flow area to frontal area | (-) |
| P | pumping water | (W) |
| σ | ratio of minimum free flow area to frontal area | (-) |
| ρ | density | (kg/m ³) |
| Sub | | |
| scri | i= input | |
| pts | O= output | |

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| Nomenclature | | |
|--------------------|--|---------------------------------------|
| A | heat transfer area | (m ²) |
| BC | baffle cut | (m) |
| C _p | specific heat in constant pressure | (J/kg K) |
| C | heat capacity rate ratio | (C _{min} /C _{max}) |
| C _{in} | total investment cost | (\$) |
| C _{op} | total operating cost | (\$) |
| C _o | annual operating cost | (\$/yr) |
| C _{total} | total cost | (\$) |
| C _L | tube layout constant | (-) |
| C _{TP} | tube count calculation constant | (-) |
| d _i | tube side inside diameter | (m) |
| d _o | tube side outside diameter | (m) |
| D _s | shell diameter | (m) |
| f | friction factor | (-) |
| G _s | fluid mass velocity based on the minimum free area | (kg/s.m ²) |
| h _i | tube side heat transfer coefficient | (W/m ² K) |
| h _o | shell side heat transfer coefficient | (W/m ² K) |
| i | annual discount rate | (%) |
| j _c | correction factor for baffle configuration | |
| j _s | correction factor for bigger baffle spacing at the shell inlet and outlet sections | |
| j _r | correction factor for the adverse temperature gradient in laminar flows | |
| j _b | correction factor for bundle and pass partition bypass streams | |
| j _l | correction factor for baffle leakage effect | |
| K _c | entrance pressure loss coefficient | (-) |
| K _e | exit pressure loss coefficient | (-) |
| k _{el} | price of electrical energy | (\$/kWh) |
| k | thermal conductivity | (W/m k) |
| L | tube length | (m) |
| L _{bc} | baffle spacing | (m) |
| m | mass flow rate | (kg/s) |
| n _p | number of tube pass | (-) |
| N _i | number of tube | (-) |
| NTU | number of transfer units | (-) |
| U | | |
| P _t | tube pitch | (m) |
| Q | heat transfer rate | (kW) |
| Re | Reynolds number | (-) |
| T | temperature | (°C) |
| U | overall heat transfer | (W/m ² K) |

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