JOURNAL OF INFORMATION SCIENCE AND ENGINEERING 36, 1155-1166 (2020)
DOI: 10.6688/JISE.202011_36(6).0001

Heat Exchanger Design using Differential Evolution-Based ABC

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The main purpose of this work is to develop a cost-effective design of the shell and tube heat exchanger (STHE). The STHE objective function to be minimized is the total cost of STHE, which is a function of the surface area of the heat transfer and pressure drop at both tube and shell side. Artificial Bee Colony (ABC) is a robust population-based swarm optimization algorithm with a few numbers of control parameters. Slow convergence and poor exploitations of ABC may cause solutions to be stuck in local minima. Differential evolution (DE) is arguably one of the most potent stochastic real-parameter optimization algorithms in current use. Compared to most other EAs, DE is much simpler and more straightforward to implement. Despite its simplicity, DE exhibits much better performance in comparison with several others on a wide variety of problems, including unimodal, multimodal, separable, non-separable, and so on. Besides, the number of control parameters in DE is very few, and the space complexity of DE is low as compared to some of the most competitive real parameter optimizers. These features help in extending DE for handling large scale and expensive optimization problems. Hybridizing ABC with DE seems a reasonable suggestion to combine the merits of both resulting in proposed Hybrid ABC DE (HABCDE). The HABCDE is compared against five algorithms using two different cases with a different number of passes, pitch type, and fluid type. The results show that HABCDE gets the minimum total cost. Total cost decreases by a percentage ranging from 22.29% to 0.93%, compared to other algorithms.

Keywords: artificial bee colony (ABC), cost optimization, differential evolution (DE), shell and tube heat exchanger (STHE), swarm optimization, particle swarm optimization, genetic algorithm

1. INTRODUCTION

Shell and tube heat exchanger (STHE) is the most common heat exchanger because it is suitable for a vast domain of pressures and temperatures. STHE is always used in many industrial applications as in power industries and petrochemical system. STHE is often used in applications that need to heat or cooling large amounts of fluid because it has features of efficient heat transfer and large surface area.

However, the optimum thermal design of STHE is not an easy problem because many related design parameters and constraints should be considered. These parameters can be divided into process and mechanical parameters [1]. Process parameters are including temperature specifications, pressure drop limits, velocity limits. Mechanical parameters are

Received December 5, 2019; revised December 14, 2019; accepted December 29, 2019.
Communicated by Mahmoud Abdel-Aty.

concerned with the selection of heat exchanger TEMA (Tubular Exchanger Manufacturers Association) layout, several passes, and specification of tube parameters [1].

Several methods have been proposed to find the optimal setting of STHE. The traditional methods [10-12] are based on trial and error calculations, so they depend strongly on the past experiences. On top of that, they are time-consuming. Recently, different evolutionary algorithms like a genetic algorithm (GA), artificial bee colony (ABC), Biogeography Based Optimization (BBO) and Particle Swarm Optimization (PSO) have been used to find the optimal parameters of STHE [2, 3, 8, 9]. However, each algorithm has its pros and cons, which is abstracted in Table 1.

Artificial Bee Colony (ABC) is an evolutionary algorithm introduced in 2005 [4]. ABC imitates the foraging behavior of the bee swarm. In ABC, the bee colony consists of three types of bees; employed, onlookers, and scouts bees. At each iteration, employee bees find the solutions randomly. Then, depending on the probability of these solutions (*i.e.*, the experience of employee bees), onlooker bees try to improve these found solutions. If the bee fails to improve the solution for some predetermined iterations, it is replaced by another random one (*i.e.*, scout) [4].

Although ABC is efficient in exploration, it has less ability to perform proper exploitation [5]. Hybridizing technique with other search algorithms as Differential Evolution (DE) is introduced to improve the performance of ABC, [6] has been introduced. Recently Hybrid ABC algorithm with Differential Evolution algorithm (HABCDE) is introduced [5]. HABCDE is tested on twenty problems and four real-world optimization problems. Results indicate that HABCDE has an excellent performance.

The main contributions of this paper are:

- Using the hybrid ABC algorithm with Differential Evolution algorithm (HABCDE) [5] to find the optimal setting of STHE.
- Comparing HABCDE against five algorithms using the total cost as the objective function.

The rest of the paper is organized as follows, Section 2 explains the related work briefly. Section 3 describes the objective function to be optimized. Section 4 describes the implementation of HABCDE to the optimal STHE design. Section 5 concludes this paper. Finally, Appendix A describes the mathematical model of STHE.

Nomenclature

a_1	numerical constant	P_r	prandtle number
a_2	numerical constant	P_t	tube pitch (m)
a_3	numerical constant	Q	heat duty (W)
B	baffles spacing (m)	Re	Reynolds number
C_l	Clearance (m)	Rf	fouling resistance (m^2K/W)
C_p	specific heat ($kJ/kg\ K$)	S	heat transfer surface area (m^2)
C_i	capital investment (€)	T	Temperature (K)
C_E	energy cost (€/$kW\ h$)	U	overall heat transfer coefficient (W/m^2K)
C_o	annual operating cost (€/$year$)	v	fluid velocity (m/s)
C_{oD}	total discounted operating cost (€)		
C_{tot}	total annual cost (€)	ΔP	pressure drop (P_a)
d	tube diameter (m)	ΔT_{LM}	logarithmic mean temperature difference(°C)
D	shell diameter (m)	μ_t	dynamic viscosity ($Pa\ s$)

f	friction factor		
F	correction factor	ρ	density (Kg/m^3)
h	heat transfer coefficient (W/m^2K)	η	overall pumping efficiency
H	annual operating time ($h/year$)		
I	annual discount rate (%)		
k	thermal conductivity (W/mK)	subscripts	
K_1	numerical constant	i	inlet
L	tubes length (m)	o	outlet
m	mass flow rate (kg/s)	s	belonging to shell
N	number of tube passages	t	belonging to tube
$n1$	numerical constant	w	tube wall
N_y	equipment life ($year$)		
N_t	number of tubes		
P	pumping power (W)		

Table 1. Pros and cons of different algorithms.

	Pros	Cons
GA	Good optimization for noisy functions [16]	Loss of diversity and premature convergence due to less effect of crossover with continuing generations [13]
DE	Relatively faster convergence [5]	– Easy to drop into local optima because of its fast convergence [13] – Very sensitive to control parameters values.
PSO	Fast convergence [13]	Easy to trap because all particles learn from best particles [13]
ABC	Good exploration [5]	– Lack of exploitation [5] – Slow convergence [5]
BBO	Powerful information sharing [15]	Poor balance of exploitation and exploration [14]

2. RELATED WORK

In this section, an overview of three related algorithms is reviewed. The algorithms are differential evolution (DE), Artificial Bee colony, and hybrid ABC with DE (HABCDE).

2.1 Differential Evolution (DE)

Differential evolution is an evolutionary algorithm introduced by Price and Storn in 1997 [6]. DE is also a kind of direction-based search that maintains a population with individuals, and has mutation, crossover operators, and a selection process. In DE, the current population members are mutated by scaled differences of randomly distinct individuals of the population. Thus, unlike GA, generating the offspring does not use separate probability distribution [7]. The simple version of DE is shown in Fig. 1.

2.2 Artificial Bee Colony (ABC)

ABC is a robust algorithm with a few control parameters and easy to implement. It is, therefore, a hot spot area for the last decade's research and development. Although it was first introduced in 2005 by Karaboga, the number of ABC publications is exponentially increasing. ABC's studies and development took two paths, either by adding a modification to the ABC standard to improve performance or by incorporating the ABC standard into other soft computing algorithms.

In ABC, the number of employee bees and onlooker bees is equal. Steps of ABC can be described in detail as the following:

1. Initialization
   Randomly initialize solutions of the employee bees = $\{x_1, x_2, x_3, \ldots, x_{NP/2}\}$.
2. Employee bee phase
   At each iteration, each employee bee searches in a straight-line direction about the solution. In its search, it depends on the random selected solution according to Eq. (4). Then a greedy selection is performed to choose the best between the new solution and the old one.

```
Begin
Randomly initialize a population of NP individuals = {X1, X2, X3, …, XNP}.
Repeat
    For each individual in the population
    Select three indexes randomly (r1 ≠ r2 ≠ r3)
    Mutate a base vector Xr1 by using a scaled difference vector (FDE is the scale vector)
```

$$V_i = X_{r1} + F_{DE}*(X_{r3} - X_{r2}) \tag{1}$$

Generate a trial vector U_i for the target vector X_i using binomial crossover (CR is the crossover rate)

$$U_{id} = \begin{cases} V_{id} & \text{If } rand[0,1] \le CR \\ X_{id} & \text{otherwise} \end{cases}. \tag{2}$$

Select the vector with the better fitness objective function value to survive into the next iteration.

$$X_i(t+1) = \begin{cases} U_i & \text{If } f(U_i) \le f(X_i) \\ X_i(t) & \text{otherwise} \end{cases} \tag{3}$$

```
    End for
    Until maximum iteration is reached
End
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Fig. 1. Pseudocode of DE algorithm.

$$Xnew_{ij} = X_{ij} + r(X_{kj} - X_{ij}) \tag{4}$$

where r is random numbers uniformly distributed in $[-1, 1]$, $Xnew$ is the new solution, i and k are random selected solution X, j is a random selected index of dimension.

3. Onlooker bee phase

In this phase, the employee bees introduce their experience to the onlooker bees to help them find a better solution. This experience measured by the probability of the solution and is calculated by Eqs. (5) and (6). As the probability of the solution increases, the chance to be selected by the onlookers increases too. After selecting the solution, the onlooker moves according to Eq. (4), and a greedy selection is applied.

$$probability_i = 0.9\frac{fitness_i}{\max(fitness)} + 0.1 \tag{5}$$

$$fitness_i = \begin{cases} \dfrac{1}{(1+f_i)} & \text{if } f_i \geq 0 \\ 1+abs(f_i) & \text{if } f_i < 0 \end{cases} \tag{6}$$

where f_i is the cost value of the solution.

4. Scout bee phase

At each iteration, ABC checks the improvement in each solution. If any solution fails to improve for a predetermined *limit* parameter, it is replaced by a random solution.

2.3 Hybrid ABC with DE (HABCDE)

To make a compromise between exploration and exploitation, HABCDE updates the equation of employee bee. It makes employee bee searches the solution using the experience of the best solution besides random solution in Eq. (7). To benefit from the fast convergence of DE, the updated equation of the onlooker bee is done using DE equation with selecting the best solution as the base vector in Eq. (8). The new solution of the onlooker is considered as a trial vector and then crossover operator and selection, as in DE, are applied.

$$Xnew_{ij} = X_{ij} + r(X_{kj} - X_{ij}) + r_2(best_j - X_{ij}) \tag{7}$$

where r_2 is random numbers uniformly distributed in [0,1], *best* is the best solution.

$$V_i = best_k + F_{DE} * (X_{r3} - X_{r2}) \tag{8}$$

3. OBJECTIVE FUNCTION

The objective function to be minimized is total cost C_{tot} of STHE [2]:

$$C_{tot} = C_i + C_{oD} \tag{9}$$

where C_i is the capital investment and C_{oD} is the total discounted operating cost. It is found that C_i is a function of the surface area of STHE:

$$C_i = a_1 + a_2 S^{a3} \tag{10}$$

where S is the surface area of heat transfer, a_1 = 8000, a_2 = 259.2, a_3 = 0.91 for stainless steel STHE. C_{oD} is a function of pumping power as in the following equations:

$$C_{oD} = \sum_{k=1}^{n_y} \frac{C_o}{(1+i)^k}, \tag{11}$$

$$C_o = P \cdot C_E \cdot H, \tag{12}$$

$$P = \frac{1}{\eta}\left(\frac{m_t}{\rho_t} \cdot \Delta P_t + \frac{m_s}{\rho_s} \cdot \Delta P_s\right), \tag{13}$$

where C_o annual operating cost, P pumping power, n_y equipment life, i annual discount rate, C_E energy cost, H annual operating time, ΔP pressure drop, m mass flow rate, ρ density, η overall pumping efficiency. For calculating S and P, please see Appendix A.

4. SETTING AND RESULTS

4.1 Setting

The design of STHE is done using the values $H = 7000$ hour/year, $i = 10\%$, $C_E = 0.12$ €/$kW\,h$, $n_y = 10$ year, $\eta = 0.8$ [2, 3, 8, 9]. STHE is tested on two different cases as shown in Table 2. In case1, the number of passes = 2 and the type of pitch type is triangular. In case 2, the number of passes = 4 and the type of pitch type is square. The parameters of HABCDE are population size = 100, number of iteration = 150, Limit = 100, $F_{DE} = 0.5$, $CR = 0.9$.

Table 2. Design specifications for different cases [8].

	m	T_i	T_o	ρ	C_p	μ	k	R_f
Case 1								
Shell side: methanol	27.8	95	40	750	2.84	0.00034	0.19	0.00033
Tube side sea water	68.9	25	40	995	4.2	0.0008	0.59	0.00020
Case 2								
Shell side: kerosene	5.52	199	93.3	850	2.47	0.0004	0.13	0.00061
Tube side crude oil	18.8	37.8	76.7	995	2.05	0.00358	0.13	0.00061

4.2 Results

HABCDE is compared against four optimization methods (*i.e.* GA [2], ABC [3], BBO [9], PSO [8]) beside the Kern design [10]. The results are shown in Tables 3 and 4. The most striking result to emerge from these tables is that HABCDE get the minimum total cost. In Case 1, the capital investment C_i is decreased by 14.94%, 11.06%, 5.69%, 1.68%, 1.63% compared to Kern design, GA, PSO, ABC, and BBO respectively. Further analysis showed that annual operating cost C_o is increased comparing to ABC and BBO algorithms due to the increase in pressure drop. The total cost C_{tot} is decreased by 22.29%, 9.02%, 5.87%, 1.35%, 0.93% compared to Kern design, GA, PSO, ABC and BBO respectively. In Case 2, the total cost C_{tot} is decreased by 28.83%, 5.29%, 3.48%, 4.92%, 2.93% compared to Kern design, GA, PSO, ABC, and BBO respectively. The cost results are shown in Figs. 2 and 3 for Cases 1 and 2 respectively.

Table 3. STHE parameters for Case 1 using different algorithms.

	Kern [10]	GA [2]	PSO [8]	ABC [3]	BBO [9]	HABCDE
D_s	0.894	0.83	0.81	1.3905	0.801	0.7134
L	4.83	3.379	3.115	3.963	2.04	1.89
B	0.356	0.5	0.424	0.4669	0.5	0.5549
d_o	0.02	0.016	0.015	0.0104	0.01	0.011
P_t	0.25	0.02	0.0187	–	0.0125	0.01375
C_l	0.005	0.004	0.0037	–	0.0025	0.00275
N_t	918	1567	1658	1528	3587	2484

v_t	0.75	0.69	0.67	0.36	0.77	0.916683
Re_t	14,925	10,936	10,503	–	7642.497	10,033.1
Pr_t	5.7	5.7	5.7	–	5.7	5.69492
h_t	3812	3762	3721	3813	4314	5137.01
f_t	0.028	0.031	0.0311	–	0.034	0.0314507
ΔP_t	6251	4298	4171	3043	6156	8992.11
a_s	0.0320	0.0831	0.0687	–	0.0801	0.0791731
D_e	0.014	0.011	0.0107	–	0.007	0.00782007
v_s	0.58	0.44	0.53	0.118	0.46	0.468172
Re_t	18,381	11,075	12,678	–	7254.007	8076.05
Pr_s	5.1	5.1	5.1	–	5.1	5.08211
h_s	1573	1740	1950.8	3396	2197	2119.11
f_s	0.330	0.357	0.349	–	0.379	0.373493
ΔP_s	35,789	13,267	20,551	8390	13.799	9538.82
U	615	660	713.9	832	755	772.064
S	278.6	262.8	243.2	–	229.95	224.938
C_i	51,507	49,259	46,453	44,559	44,536	43,810.6
C_o	2111	947	1038.7	1014.5	984	1025.05
C_{oD}	12,973	5818	6778.2	6233.8	6046	6298.52
C_{tot}	64,480	55,077	53,231.1	50,793	50.582	**50,109.1**

Table 4. STHE parameters for case 2 using different algorithms.

	Kern [10]	GA [2]	PSO [8]	ABC [3]	BBO [9]	HABCDE
D_s	0.539	0.63	0.59	0.3293	0.74	0.6471
L	4.88	2.153	1.56	3.6468	1.199	1.1
B	0.127	0.12	0.1112	0.0924	0.1066	0.1653
d_o	0.025	0.02	0.015	0.0105	0.015	0.0066
P_t	0.031	0.025	0.0187	–	0.0188	0.00825
C_l	0.006	0.005	0.0037	–	0.0038	0.00165
N_t	158	391	546	511	1061	5072
v_t	1.44	0.87	0.93	0.43	0.69	0.680546
Re_t	8227	4068	3283	–	2298	9986.92
Pr_t	5.52	5.52	5.52	–	5.52	5.52
h_t	619	1168	1205	2186	1251	1851.86
f_t	0.033	0.041	0.044	–	0.05	0.0314914
ΔP_t	49,245	14,009	16,926	1696	5109	9733.33
a_s	0.0137	0.0148	0.0131	–	0.0158	0.021393
D_e	0.025	0.0190	0.0149	–	0.0149	0.00653028
v_s	0.47	0.43	0.495	0.37	0.432	0.303561
Re_t	25,281	18,327	15,844	–	13,689	4212.47
Pr_s	7.5	7.5	7.5	–	7.5	7.5
h_s	920	1034	1288	868	1278	1388.08
f_s	0.315	0.331	0.337	–	0.345	0.411796
ΔP_s	24,909	15,717	21,745	10,667	15,275	10,634.6
U	317	367	409.3	323	317.75	361.282
S	61.5	52.9	47.5	61.566	60.35	52.9258
C_i	19,007	17,599	16,707	19,014	18,799	17,597.8
C_o	1304	440	523.3	197.139	164.414	265.617
C_{oD}	8012	2704	3215.6	1211.3	1010.25	1632.1
C_{tot}	27,020	20,303	19,922.6	20,225	19,810	**19,229.9**

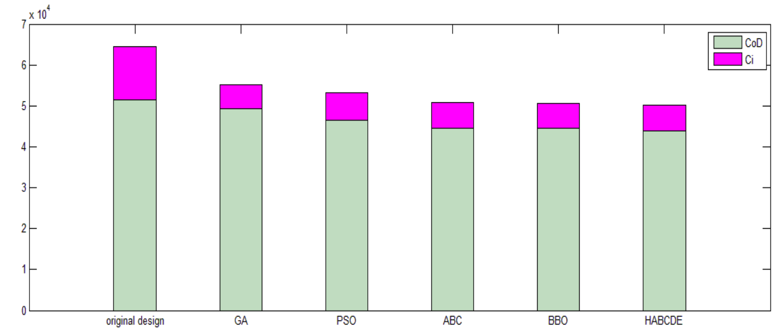

Fig. 2. Case 1 total cost for different algorithms.

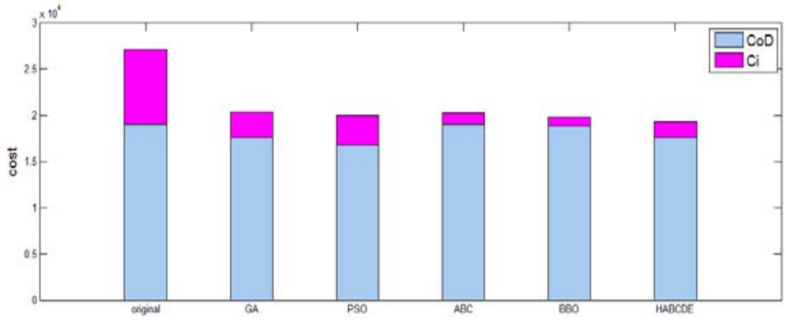

Fig. 3. Case 2 total cost for different algorithms.

5. CONCOLUSION

In literature, many algorithms are used to design STHE as GA, PSO, ABC, and BBO. However, each algorithm has its shortcomings. In this paper, a recently developed hybrid algorithm (HABCDE) is used to determine the optimal parameters of STHE. HABCDE is tested on two cases of different fluids, with different physical structures of STHE, to confirm its performance. The results are compared against five different algorithms. From the results, HABCDE can obtain the least total cost. The reduction in total cost is ranging from 22.29% to 0.93% compared to different algorithms. For future work, it is desired to consider multi objectives, besides cost, in the design problem. Many important objectives as pressure drop and velocity may be added to the design.

APPENDIX A

Tube Layout, Pitch and Clearance are calculated as in the following equations [3]:

$$P_t = 1.25 d_o \tag{A1}$$

$$d_i = 0.8 d_o \tag{A2}$$

$$a_s = \frac{D_s \cdot B \cdot C_l}{a_s \cdot \rho_s} \tag{A3}$$

$$C_l = P_t - d_o \tag{A4}$$

where B baffle spacing, P_t tube pitch, C_l clearance, d_o outside diameter of tube, D_s inside diameter of shell, a_s cross section area normal to flow direction.

(A) Calculating S [9]

$$S = \frac{Q}{U \Delta T_{LM} F} \tag{A5}$$

where Q heat transferred per unit time, U overall heat transfer coefficient, ΔT_{LM} logarithmic mean temperature difference, F correction factor.

(A.1) Calculating Q

$$Q = m_s C_{ps}(T_{is} - T_{os}) = m_t C_{pt}(T_{it} - T_{ot}) \tag{A6}$$

where m mass flow rate, C_p specific heat T_i, T_o inlet and outlet temperature respectively.

(A.2) Calculating ΔT_{LM}

For cross flow, ΔT_{LM} is calculated as:

$$\Delta T_{LM} = \frac{(T_{is} - T_{ot}) - (T_{os} - T_{it})}{\ln((T_{is} - T_{ot}) / (T_{os} - T_{it}))}. \tag{A7}$$

(A.3) Calculating F

The correction factor F for a heat exchanger which has one shell pass and two (or more even number) of tube passes is:

$$F = \frac{\sqrt{R^2+1}}{R-1} \cdot \frac{\ln\left(\dfrac{1-P_x}{1-P_x R}\right)}{\ln\left(\dfrac{2-P_x(R+1-\sqrt{R^2+1})}{2-P_x(R+1+\sqrt{R^2+1})}\right)} \tag{A8}$$

where R, P_x are calculated as the following:

$$R = \frac{T_{is} - T_{os}}{T_{ot} - T_{it}}, \tag{A9}$$

$$P_x = \frac{T_{ot} - T_{it}}{T_{is} - T_{it}}. \tag{A10}$$

(A.4) Calculating U

$$U = \frac{1}{\dfrac{1}{h_s} + R_{fs} + \dfrac{d_o}{d_i}\left(R_{ft} + \dfrac{1}{h_t}\right)} \tag{A11}$$

where R_f fouling resistance, d tube diameter, h heat transfer coefficient.
(A.4.1) calculating h_s

$$h_s = 0.36 \frac{k_s}{D_e} Re_s^{0.55} Pr_s^{\frac{1}{3}} \left(\frac{\mu_t}{\mu_w}\right)^{0.14} \tag{A12}$$

where μ dynamic viscosity, k thermal conductivity, Re Reynolds number, Pr is the Prandtle number, D_e is the hydraulic diameter of the shell. Re, Pr and D_e are calculated as in the next equations:

$$D_e = \frac{4(P_t^2 - (\pi d_o^2/4))}{\pi d_o^2}\text{; for square pitch} \tag{A13}$$

$$D_e = \frac{4(0.43P_t^2 - (0.5\pi d_o^2/4))}{0.5\pi d_o^2}\text{; for triangular pitch} \tag{A14}$$

$$Pr_s = \frac{\mu_s C_{ps}}{k_s} \tag{A15}$$

$$Re_s = \frac{\rho_s v_s D_e}{\mu_s} \tag{A16}$$

ρ_s density, v is the fluid velocity and is calculated by:

$$v_s = \frac{m_s}{a_s \rho_s} \tag{A17}$$

(A.4.2) calculating h_t

$$h_t = \frac{k_t}{d_i}\left[3.657 + \frac{0.0677(Re_t Pr_t \frac{d_i}{L})^{1.33}}{1+0.1Pr_t(Re_t \frac{d_i}{L})^{0.3}}\right]; \tag{A18}$$

For $Re_t < 2300$

$$h_t = \frac{k_t}{d_i}\left(\frac{\frac{f_t}{8}(Re_t - 1000)Pr_t}{(1+12.7\sqrt{\frac{f_t}{8}}(\mathrm{Pr}_t^{\frac{2}{3}} - 1)}\left[1 + (\frac{d_i}{L})^{0.67}\right]\right); \tag{A19}$$

For $2300 > Re_t < 10000$

$$h_t = 0.027 \frac{k_t}{d_i} Re_t^{0.8} Pr_t^{\frac{1}{3}} \left(\frac{\mu_t}{\mu_w}\right)^{0.14}; \tag{A20}$$

For $Re_t > 10000$.

where L is the tubes length, f friction factor, Re_t, Pr_t and f are calculated in the following equations:

$$Pr_t = \frac{\mu_t C_{pt}}{k_t} \tag{A21}$$

$$Re_t = \frac{\rho_t v_t d_i}{\mu_t} \tag{A22}$$

where v is the fluid velocity and can be calculated as:

$$v_t = \frac{m_t}{\frac{\pi d_i^2}{4}\rho_t}\frac{n}{N_t} \tag{A23}$$

N_t is the number of tubes:

$$N_t = K_1\left(\frac{D_s}{d_o}\right)^{n1} \tag{A24}$$

where K_1, n_1 are coefficients depends on number of passes n and flow arrangement. For $n = 2$; square tube pitch $K_1 = 0.249$; $n1 = 2.207$. For $n = 4$; triangular tube pitch $K_1 = 0.158$; $n1 = 2.263$.

$$f_t = (1.82\log_{10}Re_t - 1.64)^{-2} \tag{A25}$$

(A) Calculating $P[3, 9]$

(B.1) Calculating ΔP_s

$$\Delta P_s = f_s \cdot \left(\frac{\rho_s v_s^2}{2}\right)\cdot\left(\frac{L}{B}\right)\cdot\left(\frac{D_s}{D_e}\right) \tag{A26}$$

where f_s friction factor and is calculated as:

$$f_s = 2b_0 Re_s^{-0.15} \tag{A27}$$

where Re Reynolds number, $b_0 = 0.72$ if $Re < 40000$

(B.2) Calculating ΔP_t

$$\Delta P_t = \Delta P_{tube\ length} + \Delta P_{tube\ elbow} \tag{A28}$$

$$\Delta P_i = \frac{\rho_t v_t^2}{2}\left(\frac{L}{d_i} f_t + p\right)\cdot n \tag{A29}$$

Kern assumes that $p = 4$ [10].

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