Optimization of Shell and Tube Heat Exchangers using Teaching-Learning based Optimization Algorithm

Bansi D. Raja
Department of Mechanical Engineering
Indus University
Ahmedabad, Gujarat, India

R. L. Jhala
Department of Mechanical Engineering
Marwadi Education Foundation
Rajkot, India

Abstract **— This study explores the application of teaching-learning based optimization (TLBO) algorithm, a recently developed advanced optimization technique, for design optimization of shell and tube heat exchangers from economic view point. Minimization of total annual cost is considered as an objective function. Three design variables such as shell internal diameter, outer tube diameter and baffle spacing are considered for optimization. Two different case studies are also presented to demonstrate the effectiveness and accuracy of the proposed algorithm. The results of optimization obtained using TLBO algorithm is compared with those obtained by using other optimization algorithm.**

Keywords— Teaching-lerning based optimization algorithm; Shell and tube heat exchanger; optimization;

INTRODUCTION

Heat exchangers are used in industrial process to recover heat between two process fluids. Shell and tube heat exchanger (STHE) are the most widely used heat exchangers in process industries The design of STHEs, including thermodynamic and fluid dynamic design, cost estimation and optimization, represent a complex process containing an integrated whole of design rules and empirical knowledge of various fields [1, 2].The design of 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.

There are many previous studies on the optimization of heat exchanger. Several investigators had used different optimization techniques considering different objective functions to optimize heat exchanger design. Selbas et al. [2] used genetic algorithm (GA) for optimal design of STHEs, for achieving optimal design parameters. Ozcelik [3] considered mixed integer nonlinear programming problem of STHE taking in to account the sizing and exergy cost of the STHE. Caputo et al. [4] carried out heat exchanger design based on economic optimization using GA. Fesanghary et al. [5] carried out the optimization of influential parameter of STHE from economic point of view by applying harmony search algorithm. Wildi-Tremblay and Gosselin [6] used GA to minimize the STHE cost. The author had considered the maintenance of STHE also. Rao and Patel [7] used Particle swarm optimization (PSO) algorithm for the design optimization of shell and tube heat exchanges. Caputo et al. [8] carried out comparison between actual installed heat exchangers, designed resorting to a leading commercial software tool, and the corresponding equipment configurations obtained by a genetic algorithm-based software tool, developed for optimal heat exchangers design. Asadi et al. [9] approach the design optimization problem of STHE using Cuckoo-search-algorithm. Hadidi and Nazari [10, 11] adopt the biogeography-based algorithm and imperialist competitive algorithm to solve the STHE problem from economic view point. Several other investigators [12-19] used different strategies for various objectives to optimize shell and tube heat exchanger design.

The main objectives of this study are to optimize the influential parameter of STHEs from economic point of view using recently developed teaching-learning based optimization (TLBO) algorithm. Ability of the considered algorithm is demonstrated using two different case studies. The results obtained using the TLBO are compared with those obtained by using GA and traditional method.

MATHEMATICAL MODELING OF SELL AND TUBE HEAT ESCHANGERS

Evolution of heat exchanger performance in the present work is based on Kern’s methodology.

A. Tube-side heat transferand pressure drop

According to flow regime, the tube side heat transfer coefficient (h_t) is computed from following correlation,

$$h_t = \frac{k_t}{d_i}\left[1.86\left(\frac{\mathrm{Re}_t\,\mathrm{Pr}_t\,d_i}{L}\right)^{1/3}\right]\left(If\ Re_t < 2300\right) \quad (1)$$

$$h_t = \frac{k_t}{d_i}\left[\frac{\frac{f}{2}\mathrm{Re}_t\,\mathrm{Pr}_t}{1.07+12.7\left(\frac{f}{2}\right)^{0.5}\left(\mathrm{Pr}_t^{2/3}-1\right)}\right](2300<\mathrm{Re}_t<10^4) \quad (2)$$

$$h_t = 0.023\frac{k_t}{d_i}\mathrm{Re}_t^{0.8}\,\mathrm{Pr}_t^{1/3}\left(\frac{\mu_t}{\mu_w}\right)^{0.14}\quad For\ Re_t > 10000 \quad (3)$$

Flow velocity for tube side is found by,

$$v_t = \frac{4m_t}{\pi d_t^2 \rho_t}\left(\frac{N_P}{N_t}\right) \tag{4}$$

N_t is number of tubes and N_P is the number of tube passes. Tube side pressure drop include distributed pressure drop along the tube length and concentrated pressure losses in elbows and in the inlet and outlet nozzle [1].

$$\Delta P_t = \frac{\rho_t v_t^2}{2}\left(\frac{L}{d_i} f_t + p\right) N_p \tag{5}$$

Constant p is given different values by different authors. Kern [1] suggested p = 4 and same value utilized in the present work.

B. Shell-side heat transferand pressure drop

Kern's formulation for segmental baffle shell and tube exchanger is used for computing shell side heat transfer coefficient h_s [1].

$$h_s = 0.36 \frac{k_t}{d_e} \mathrm{Re}_s^{0.55} \mathrm{Pr}_s^{1/3} \left(\frac{\mu_s}{\mu_{wts}}\right)^{0.14} \tag{6}$$

Where, d_e is the shell hydraulic diameter. Cross section area normal to flow direction is determined by [1],

$$A_s = D_s B \left(1 - \frac{d_o}{S_t}\right) \tag{7}$$

Where, D_s is the shell diameter, d_o is the tube diameter, B is baffle spacing and S_t is the tube pitch.

The overall heat transfer coefficient (U) depends on both the tube side and shell side heat transfer coefficient and correction factor F is calculated using [1] as,

$$U = \frac{1}{\left(\frac{1}{h_s}\right) + R_{fs} + \frac{d_o}{d_i}\left(R_{ft} + \frac{1}{h_t}\right)} \tag{8}$$

Where, R_{fs} and R_{ft} is the shell side and tube side fouling factor respectively. Considering overall heat transfer coefficient, the heat exchanger surface area (A) is computed by,

$$A = \frac{Q}{U\,F\,LMTD} \tag{9}$$

Where, F is the fouling factor. The length of heat exchanger is calculated using this heat transfer area calculated from the above equation. The shell side pressure drop is estimated by,

$$\Delta P_s = f_s \left(\frac{\rho_s v_s^2}{2}\right)\left(\frac{L}{B}\right)\left(\frac{D_s}{d_e}\right) \tag{10}$$

Considering pumping efficiency (η), pumping power (P) computed by.

$$P = \frac{1}{\eta}\left(m_t \Delta P_t + m_s \Delta P_s\right) \tag{11}$$

Where, m_t and m_s is the tube side and shell side mass flow rate respectively in kg/s.

C. Cost estimation

Adopting Hall's correlation [20], the capital investment C_i is computed as a function of the exchanger surface area.

$$C_i = a_1 + a_2 A^{a/3} \tag{12}$$

Where, a_1 = 8000, a_2 = 259.2 and a_3 = 0.93 for exchanger made with stainless steel for both shell and tubes [20].

The total discounted operating cost related to pumping power to overcome friction losses is computed from the following equation,

$$C_o = P\,C_e H \tag{13}$$

$$C_{od} = \sum_{x=1}^{ny} \frac{C_o}{(1+i)^x} \tag{14}$$

Where, C_o and C_{od} is the annual operating cost (€/yr) and total discounted operating cost (€). H is the annual operating time (h/yr) and i is the annual discount rate (%).

D. Objective function

Total cost C_{tot} is taken as the objective function, which includes capital investment (C_i), energy cost (C_e), annual operating cost (C_o) & total discounted operating cost (C_{od}) [4].

$$C_{tot} = C_i + C_{od} \tag{15}$$

Above equation is considered as objective function in the present work. The procedure is repeated computing new value of exchanger area (A), exchanger length (L), total cost (C_{tot}) and a corresponding exchanger architecture meeting the specifications. Each time the optimization algorithm changes the values of the design variables d_o, D_s and B in an attempt to minimize the objective function.

TEACHING LEARNING BASED OPTIMIZATION ALGORITHM (TLBO)

Teaching-learning method is the core of any education system. Inspired by the idea of teaching and learning, Rao et al. [21-22] introduced an innovative approach called teaching-learning-based optimization (TLBO) algorithm. The algorithm simulates two fundamental modes of learning: (i) through teacher and (ii) interacting with the other learners. TLBO is a population based algorithm where a group of students (i.e learner) is considered as population and the different subjects offered to the learners is analogous with the different design variables of the optimization problem. The grades of a learner in each subject represent a possible solution to the optimization problem (value of design variables). The best solution in the entire population is considered as the teacher. The working of TLBO algorithm is split in to two parts as explained below.

E. Teacher phase

In this section of the algorithm, learners learn through a teacher. The mean of class depends on the quality of learners. A good teacher tries to bring the level of learners to his or her level in terms of knowledge, but to achieve the same level not only depends on the teacher but also depends on the capability of learners in the class to capture the knowledge shared by the teacher. So, it follows the random process depending on different factors.

Assume that number of learners (i.e. population) is n, number of subject (i.e. design variables) is m, M is the mean of the learners (population) and T *be* the teacher (best solution). T will try to move M toward its level. Let T_F is a teaching factor that decide the value of the mean to be changed, and r is a random number whose value is in the range of [0, 1]. The solution is modified in the teacher phase according to the difference between the existing and the new mean. The Modified solution is expressed as:

$$A_{i,j}^{new} = A_{i,j}^{old} + r_{ij}\left(T_j - T_F M_j\right) \tag{16}$$

Where, $i=1,2,\ldots,n$, $j=1,2,\ldots,m$. T_F is set to either 1 or 2 and decided randomly with equal probability given as T_F = *round[1 + rand(0, 1){2-1}]*.

F. Learne phase

In the second section of the algorithm, Learners increase their knowledge through the interaction between themselves. A learner interrelates randomly with other learners with the help of formal communications, presentations, group discussions, etc. A learner learns something better or new if the other learner has better knowledge than him/her.

In the learning phase, two random solutions i &k are selected and the solution is updated as:

If $(f(A_i) < f(A_k))$

$$A_{i,j}^{new} = A_{i,j}^{old} + r_{ij}\left(A_{i,j}^{old} - A_{k,j}^{old}\right) \text{ where } i \neq k \tag{17}$$

Else

$$A_{i,j}^{new} = A_{i,j}^{old} + r_{ij}\left(A_{k,j}^{old} - A_{i,j}^{old}\right) \text{ where } i \neq k \tag{18}$$

Accept if it gives better function value. Next section describe the application of TLBO algorithm for the design optimization of STHE/

CASE STUDY AND RESULT DISCUSSION

The usefulness of the present approach using TLBO in design optimization of Shell and tube heat exchanger is assessed by analyzing two case studies which was earlier assess by Caputo et al. [4] using GA approach. The schematic diagram of STHE with tube pitch pattern is shown in Fig.1.

Case-1: 4.34(MW) duty, methanol – Sea water exchanger
Case-2: 1.44(MW) duty, kerosene – crude oil exchanger.

The original design specifications, shown in Table 1 were supplied as an input to the described algorithm for both the cases. The resulting optimal exchanger's architectures obtained by TLBO were compared with the results obtained using GA and with original design solution given by the Kern [1]. In order to allow a consistence comparison, cost function of all the approaches were computed as described in previous section. In the TLBO approach following upper and lower bounds for the optimization variables were imposed: Shell inside diameter (D_s) ranging between 0.1 m to 1.5 m; Tubes outer diameter (d_o) ranging between 0.015 m to 0.051 m; Baffle spacing (B) ranging from 0.05 m to 0.5 m. All value of discounted operating costs were computed with ny =10 yr, annual discount rate (i) =10%, energy cost (C_e) =0.12 €/kW h and an annual amount of work hours H =7000 y/hr. Moreover, the proposed algorithm is implemented.

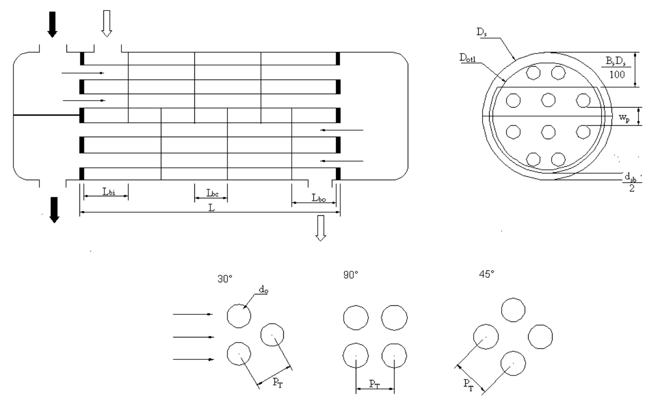

Fig.1 STHE geometry with tube pitch pattern arrangement

Table 2 shows the optimized parameters of the first case study obtained using TLBO and its comparison with the optimized parameters obtained using GA and traditional method.

TABLE 1. PROCESS INPUT AND PHYSICAL PROPERTIES

	Case-1		Case-2	
	Shell Side: Methanol	Tube side: Sea water	Shell Side: Kerosene	Tube side: Crude oil
Mass flow (kg/s)	27.80	68.90	5.52	18.80
T_{input} (^{0}C)	95.00	25.00	199.00	37.80
T_{output} (^{0}C)	40.00	40.00	93.30	76.70
Density (kg/m^3)	750.00	995.00	850.00	995.00
Specific heat (KJ/kg K)	2.84	4.20	2.47	2.05
Viscosity (Pa s)	0.00034	0.0008	0.0004	0.00358
Thermal conductivity (W/m K)	0.19	0.59	0.13	0.13
Fouling resistance	0.00033	0.0002	0.00061	0.00061

It is observed from the result that a significant increase in number of tubes reduces the tube side flow velocity which consecutively reduces the tube side heat transfer coefficient in the present approach. The reduction in shell diameter increases the shell side flow velocity which consecutively increases the shell side heat transfer coefficient in the present approach. So, the overall effect of this higher shell side heat transfers coefficient result in increase in overall heat transfer coefficient which in turn leads to reduction in heat exchanger area and length in the present approach. Because of reduction in heat exchanger area the capital investment is also decreased corresponding to 4.83% in the present approach. The reduction in tube side flow velocity reduces the tube side pressure drop while the high shell side flow velocity increases the shell side pressure drop. Therefore, increment in the annual pumping cost about 4.55% was observed in the present case. Overall the combined effect of capital investment and operating costs led to a reduction of the total cost of 3.82% in the present approach as compared to GA approach.

TABLE 2. PROCESS INPUT AND PHYSICAL PROPERTIES

Output Parameters	*Literature Value*	*GA [4]*	*TLBO*
L (m)	4.83	3.379	3.283
d_o (m)	0.02	0.016	0.015
B (m)	0.356	0.5	0.5
D_s (m)	0.894	0.83	0.7953
S_t (m)	0.025	0.02	0.0187
N_t	918	1567	1592
v_t (m/s)	0.75	0.69	0.6769
Re_t	14925	10936	10772.2
f_t	0.028	0.031	0.0308
ΔP_t (Pa)	6251	4298	5426.1
v_s (m/s)	0.58	0.44	0.466
Re_s	18381	11075	10976.3
f_s	0.33	0.357	0.3567
ΔP_s (Pa)	35789	13267	14211
U (W/m^{2}K)	615	660	705.4
A (m^2)	278.6	262.8	246.18
C_i (€)	51507	49259	46876.8
C_{od} (€)	12973	5818	6095.8
C_{tot} (€)	64480	55077	52972.6

Fig. 2 shows the convergence of the objective function using both the approaches. It is observed from the figure that the convergence rate of TLBO algorithm is very fast compared to GA approach.

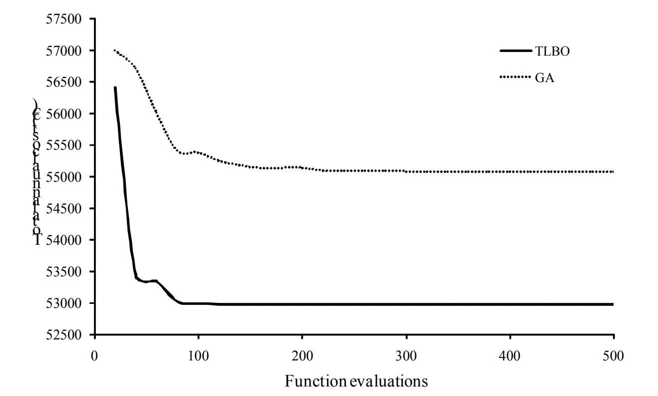

Fig. 2 Convergence of GA and TLBO algorithms

Table 3 shows the comparison of the optimized parameter obtained for the second case study using present approach with the earlier optimized parameter obtained using GA and traditional method. The original design assumed a heat exchanger with four tube side passage (with square pitch pattern) and one shell side passage. The same configuration is retained in the present approach. In this case higher tube side flow velocity increases the tube side heat transfer coefficient; similarly high shell side flow velocity increases the shell side heat transfer coefficient. Because of combined increment in tube side and shell side heat transfer coefficient an 8.85% increment in overall heat transfer coefficient was observed in the present approach. As a result of high overall heat transfer coefficient, reduction in heat exchanger area and length was observed in the present approach. The capital investment therefore decreased by 5.1% in the present approach. The higher tube side and shell side flow velocity increases the tube side and shell side pressure drop. Therefore, increment in the pumping cost was observed in the present case. Overall the reduction in capital investment and increment in pumping cost results in 1.87% reduction in total investment is observed using present approach.

TABLE 3. COMPARISON OF THE HEAT EXCHANGER DESIGN

Output Parameters	*Literature Value*	*GA [4]*	*TLBO*
L (m)	4.88	2.153	1.56
d_o (m)	0.025	0.02	0.015
B (m)	0.127	0.12	0.1112
D_s (m)	0.539	0.63	0.59
S_t (m)	0.031	0.025	0.0187
N_t	158	391	646
v_t (m/s)	1.44	0.87	0.93
Re_t	8227	4068	3283
f_t	0.033	0.041	0.044
ΔP_t (Pa)	49245	14009	16926
v_s (m/s)	0.47	0.43	0.495
Re_s	25281	18327	15844
f_s	0.315	0.331	0.337
ΔP_s (Pa)	24909	15717	19745
U (W/m^{2}K)	317	376	409.3
A (m^2)	61.5	52.95	47.5
C_i (€)	19007	17599	16707
C_{od} (€)	8012	2704	3215.6
C_{tot} (€)	27020	20303	19922.6

Fig. 3 shows the convergence of the objective function using both the approaches. Here also convergence rate of TLBO algorithm is very fast compared to GA approach.

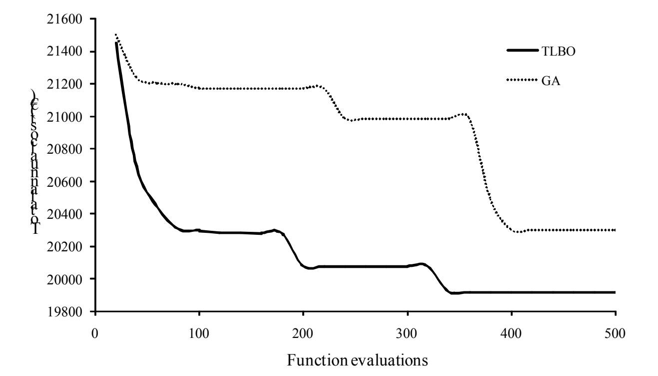

Fig.3 Convergence of PSO, CSO and HTS algorithms

Overall, the combined effect of reduction in capital investment and increment in operating costs result in reduction of the total cost of about 4.33% (compared to GA), 0.82% (compared to PSO), 0.32% (compared to CSO) observed using proposed algorithm. Fig. 2 shows the convergence of the objective function using all the approaches. It is observed from the figure that the convergence rate of HTS algorithm is very fast compared to rest of the approaches.

CONCLUSION

This study demonstrates successful application of TLBO algorithm for the optimal design of shell and tube heat exchanger from economic view point. In the present work three design variables were optimize in order to identify the cheapest possible solution. The algorithm's ability was demonstrated using a case study and the performance is compared with GA and traditional method. Referring to results, saving in total cost observed using TLBO as compared to GA and traditional method. Moreover, TLBO converge to optimum value of the objective function within few function evaluations which shows the improvement potential of the TLBO algorithm for heat exchanger optimization. Furthermore, TLBO is simple in concept, few in parameters and easy for implementation. These features boost the applicability of the TLBO algorithm particularly in thermal system design, where the problems are usually complex and have a large number of variables and discontinuity in the objective function

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