

Thermal Design and Constrained Optimization of a Fin and Tube Heat Exchanger Using Differential Evolution Algorithm

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Abstract *Fin and tube heat exchangers (FTHEs) are utilized for gas-liquid applications frequently. In the current study, a differential evolution (DE) algorithm and JDE as its variant, with α-level constraint-handling technique, are effectively applied to optimize an FTHE. Total weight and total annual cost are selected as objective functions. Seven design variables are taken into consideration: outside tube diameter, transverse pitch, longitudinal pitch, fin pitch, number of tube rows, height, and width of shape. Meanwhile, the logarithmic mean temperature difference (LMTD) method is used for heat transfer analysis under identical conditions such as mass flow rate, inlet and outlet temperatures, heat duty, and other thermal properties. The research findings indicate that the implementation of the DE algorithm coupled with α-level comparison method on optimization problems leads to better solutions for both objective functions compared with those achieved by other approaches such as the genetic algorithm (GA) and heat transfer search (HTS) algorithm. In addition, a parametric analysis is performed for design parameters at the optimum points to show the effects on the objective functions and to identify the feasible design space. The proposed method is straightforward and can generally be employed for thermal design and optimization of FTHEs as well as any other type of compact heat exchangers (CHEs) under different specified duties.*

Keywords *Fin and tube heat exchanger, thermal design, constrained optimization, differential evolution (DE) algorithm, total weight, total annual cost*

Highlights

- *Compact heat exchangers aim to minimize weight and annual cost in industrial use.*
- *Metaheuristic algorithms outperform trial-and-error methods in optimization.*
- *Differential evolution with α-level constraints achieves superior optimization results.*
- *Proposed method cuts weight by 9.33% and cost by 6.87 % from previous best results.*

1 INTRODUCTION

The process of heat exchange between two fluids that are at different temperatures and separated by a solid wall occurs in many engineering applications. The device used to implement this exchange is termed a heat exchanger (HE), and specific applications may be found in space heating and air-conditioning, power production, waste heat recovery, and chemical processing [1]. The area density is the ratio of heat transfer surface to HE volume. A compact heat exchanger (CHE) has a high area density compared to traditional HEs. CHEs are highly effective and low in weight and cost. Fins are used on the gas side of CHEs to compensate for high thermal resistance and enhance the heat transfer coefficient. Plate-fin heat exchangers (PFHEs), fin and tube heat exchangers (FTHEs), and rotary regenerators are examples of CHEs for gas flow on one or both fluid sides [2].

The most common criteria for the optimization of CHEs are the minimum initial cost, minimum operation cost, maximum effectiveness, minimum pressure drop, minimum heat transfer area, minimum weight, or material. The optimization of a CHE can be transformed into a constrained optimization problem and then solved by modern optimization algorithms [3].

The following could be highlighted after looking into the studies accomplished on the thermal design and optimization of PFHEs: Rao and Patel [4] applied the particle swarm optimization (PSO) algorithm for the thermodynamic optimization of a PFHE based on three individual objective functions: total number of entropy generation units, total volume, and total annual cost. Ahmadi et al. [5] used the ε-NTU method and a nondominated sorting genetic algorithm (GA) for the thermal modeling of a PFHE to minimize cost and entropy generation. Wang and Li [6] introduced and carried out an improved multi-objective cuckoo search (IMOCS) algorithm for multi-objective optimization, including efficiency maximization, minimization of pumping power, and total annual cost. Hajabdollahi [7] compared two cases of similar and non-similar fins on each side of the PFHE by using a PSO algorithm for thermo economic optimization.

If one fluid is a liquid, different fin and tube configurations are frequently used; the liquid passes through the tubes while the gas flows across the bank of finned tubes. Various tube shapes might be used such as circular tubes, ovals, rectangles, and any other complex type. Compressor inter-coolers, air-coolers, and fan coils are examples of power engineering and chemical applications that employ FTHEs. Xie et al. [8] and Raja et al. [9] were seeking to achieve the optimal design of an FTHE based on total weight and total annual cost by employing GA and heat transfer search (HTS) algorithms, respectively.

Compared to most other evolutionary algorithms (EAs), differential evolution (DE) is much simpler and more straightforward to implement. The main body of the algorithm takes a few lines to code in any programming language. Also, the performance of DE and its variants is largely better than other optimization algorithms such as PSO, PCX, ALEP, etc. [10]. Babu et al. [11] applied DE algorithm and its various strategies for the optimal design of shell and tube heat exchangers. Ayala et al. [12] proposed a novel multi

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objective free search (FS) approach combined with DE (MOFSDE) algorithm for heat exchanger optimization. Segundo et al. [13] by considering a shell-and-tube heat exchanger and the total annual cost as the objective function, employed DE algorithm, and Tsallis differential algorithm (TDE) to optimize it. Also, Yuan et al. [14] compared two helically coiled tubes' heat transfer characteristics and hydrodynamics by implementing an adaptive multi-objective optimization DE algorithm.

Now, what is the best solution? Perhaps, this is the main question that arises in an engineering optimization problem. However, in most discussed thermal design and optimization studies about CHEs, penalty function-based methods are employed to handle the constraints and seldom can achieve a global solution that satisfies all constraints. Differential evolution with Level Comparison (DELC) for the first time is proposed by Wang and Li [15] and achieves superior searching quality on all the problems with fewer evaluation times than other algorithms. In this paper, DELC and JDE as a variant of standard DE with level comparison (JDELC) are applied to the thermal design and optimization problem of an FTHE.

The remainder of this paper is organized as follows: In Section 2, an FTHE is modeled by using a closed-form equation to predict the heat transfer coefficient. The next section introduces objective functions including total weight and total annual cost in addition to corresponding constraints. Section 4 is about the traditional design method used for FTHEs. Section 5 demonstrates the DE algorithm and employs DE and JDE based on the α-level constraint-handling technique. Section 6 illustrates a case study of FTHE and explains the results and discussion. In Section 7, a parametric analysis is carried out to obtain feasible design space. Finally, the conclusions are delivered in Section 8, followed by the list of symbols and the list of references.

2 THERMAL DESIGN

In the present work, an intercooler is considered as an FTHE with a plain-fin type in which hot air flows normally to a finned tube bundle while cold water flows inside tubes, as illustrated in Fig. 1. However, it is common to use other types of fins, such as wavy, slotted, and louvered.

2.1 Heat Transfer

For the geometry calculations of staggered tube arrangement, the minimum free flow area on the airside is given by the following Eq. (1) [2]:

$$A_{min} = \left[\left(\frac{H}{P_t} - 1 \right) c + \left(P_t - d_o \right) \left(1 - t_f N_f \right) \right] W, \tag{1}$$

where

$$\begin{cases} c = 2a & \text{if} \quad 2a < 2b \\ c = 2b & \text{if} \quad 2b < 2a \end{cases}. \tag{2}$$

Values of $2a$ and b are determined as follows:

$$2a = \left(P_t - d_O \right) \left(1 - t_f N_f \right), \tag{3}$$

$$b = \left(\left(0.5 P_t \right)^2 + P_l^2 \right)^{0.5} - d_o - \left(P_t - d_o \right) t_f N_f . \tag{4}$$

The total heat transfer area of the heat exchanger is calculated as:

$$A = A_p + A_f , \tag{5}$$

where, A_p and A_f are the primary and secondary (i.e., fin) surface area of the heat exchanger, respectively, and obtained by,

$$A_p = \pi d_o W N_t \left(1 - t_f N_f \right), \tag{6}$$

$$A_f = 2 N_f W \left(LH - \frac{\pi}{4} d_o^2 N_t \right) + 2 t_f N_f W H , \tag{7}$$

where N_t is the number of tubes and N_f is the number of fins per unit length and defined as follows:

$$N_t = \left(\frac{H}{P_t} - 1 \right) N , \tag{8}$$

$$N_f = \frac{\frac{W}{F_p} + 1}{W} . \tag{9}$$

For the air side, when number of tube rows is greater than one, the Colburn factor (j_a) correlation is suggested by Wang [16]:

$$j_a = 0.086 Re_{d_c}^{j3} N^{j4} \left(\frac{F_p}{d_c} \right)^{j5} \left(\frac{F_p}{d_h} \right)^{j6} \left(\frac{F_p}{P_t} \right)^{-0.93} , \tag{10}$$

where j_3 to j_6 is calculated by the following formulations:

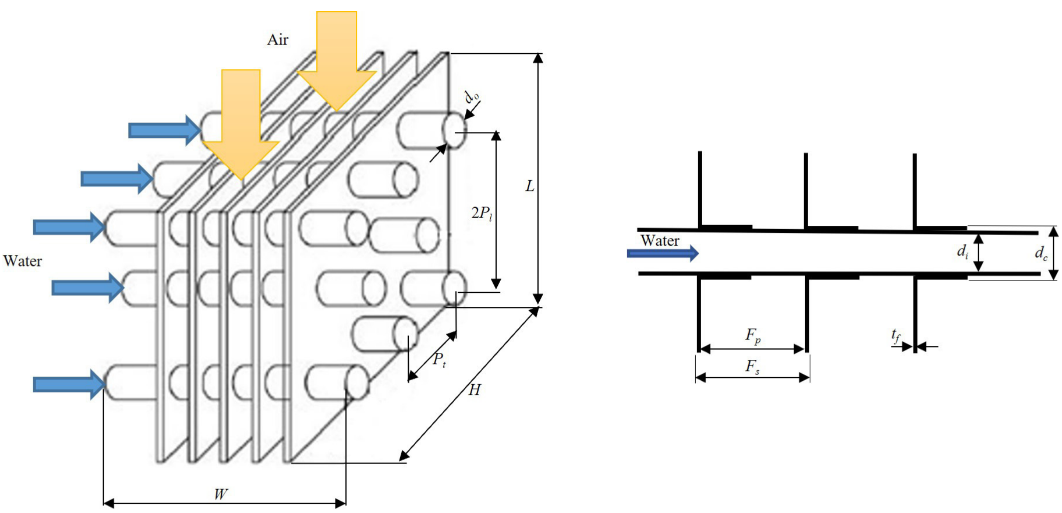

Fig. 1. Fin and tube heat exchanger with cross section view

$$j_3 = -0.361 - \frac{0.042N}{\ln\left(Re_{dc}\right)} + 0.158\ln\left(N\left(\frac{F_p}{d_c}\right)^{0.41}\right), \tag{11}$$

$$j_4 = -1.224 - \frac{0.076\left(\frac{P_l}{d_h}\right)^{1.42}}{\ln\left(Re_{dc}\right)}, \tag{12}$$

$$j_5 = -0.083 + \frac{0.058N}{\ln\left(Re_{dc}\right)}, \tag{13}$$

$$j_6 = -5.735 + 1.21\ln\left(\frac{Re_{dc}}{N}\right), \tag{14}$$

then the heat transfer coefficient on the air side can be achieved by,

$$h_a = j_a \frac{\rho_a \vartheta_a c_{p,a}}{Pr_a^{0.67}}. \tag{15}$$

For the water side, the heat transfer area can be computed by the following relationship:

$$A_i = \pi d_i W N_t. \tag{16}$$

The Nusselt number was approximated through the correlation given by Gnielinski [17]:

$$Nu_w = \frac{\frac{f_w}{8}\left(Re_w - 1000\right)Pr_w}{1 + 12.7\left(\frac{f_w}{8}\right)^{1/2}\left(Pr_w^{2/3} - 1\right)}, \tag{17}$$

where f_w is the friction factor and obtained by,

$$f_w = \left(1.82\, log_{10}^{Re_w} - 1.64\right)^{-2}. \tag{18}$$

The heat transfer coefficient on the water side is as follows:

$$h_w = \frac{Nu_w k_w}{d_i}. \tag{19}$$

The basic equation for the design of FTHE is developed in the Eq. (20) [18],

$$Q = UA \cdot T_m = U_o A_o \cdot T_m = U_i A_i \cdot T_m, \tag{20}$$

under dry cooling conditions,

$$\frac{1}{UA} = \frac{1}{\eta_i h_i A_i} + R_{fi} + \frac{ln\left(\frac{d_o}{d_i}\right)}{2\pi k_t W N_t} + R_{fo} + \frac{1}{\eta_o h_o A_o}, \tag{21}$$

where, R_{fi} and R_{fo} are the fouling resistances of inside and outside tubes, respectively, and assumed negligible, η_i and η_o are the fin efficiencies of inside and outside tubes, respectively. The air side fin efficiency is calculated from the modified Schmidt equation that has been proposed by Hong and Webb [19],

$$\eta_f = \frac{\tanh\left(m r \phi\right)}{m r \phi} cos\left(m r \phi\right), \tag{22}$$

where

$$m = \sqrt{\frac{2h}{t_f k_f}}, \tag{23}$$

$$\phi = \left(\frac{r_{f,eq}}{r} - 1\right)\left(1 + 0.35\ln\left(\frac{r_{f,eq}}{r}\right)\right). \tag{24}$$

For rectangular fins, the equivalent radius is introduced by Schmidt in the following correlation [20],

$$\frac{r_{f,eq}}{r} = 1.28\frac{p_t/2}{r}\left(\sqrt{\frac{P_l}{P_t} - 0.2}\right), \tag{25}$$

where r is the radius of the tube based on the outside tube diameter. Then the air side surface efficiency can be obtained by,

$$\eta_o = 1 - \left(\frac{A_f}{A_O}\right)\left(1 - \eta_f\right). \tag{26}$$

Here, the logarithmic mean temperature difference (LMTD) method is applied for heat exchanger analysis.

$$Q = UA \cdot T_{lm}. \tag{27}$$

LMTD is the maximum temperature potential through the heat transfer process that occurs in a counterflow heat exchanger and is described as the following expression:

$$\Delta T_{lm} = \frac{\Delta T_1 - \Delta T_2}{\ln\frac{\Delta T_1}{\Delta T_2}}, \tag{28}$$

where

$$\Delta T_1 = T_{h,i} - T_{c,o}, \tag{29}$$

$$\Delta T_2 = T_{h,o} - T_{c,i}. \tag{30}$$

For a crossflow arrangement, Eq. (27) is modified with a correction factor F_c,

$$Q = UAF_c \Delta T_{lm}. \tag{31}$$

The correction factor F_c is determined from charts or formulas based on two dimensionless parameters: temperature effectiveness P, and the ratio of heat capacity rates, R. Details of calculating these parameters can be found in fundamentals of heat exchanger design [2].

2.2 Pressure Drop

On the air side, the friction factor is obtained from the following correlation given by Wang [16],

$$f_a = 0.0267 Re_{d_c}^{f1}\left(\frac{P_t}{P_l}\right)^{f2}\left(\frac{F_p}{d_c}\right)^{f3}, \tag{32}$$

where

$$f_1 = -0.764 + 0.739\frac{P_t}{P_l} + 0.177\frac{F_p}{d_c} - \frac{0.00758}{N}, \tag{33}$$

$$f_2 = -15.689 + \frac{64.021}{\ln\left(Re_{dc}\right)}, \tag{34}$$

$$f_3 = 1.696 - \frac{15.695}{\ln\left(Re_{dc}\right)}, \tag{35}$$

$$Re_{dc} = \frac{G_a d_c}{\mu_a}, \tag{36}$$

where G_a is the mass velocity of air regarding minimum free flow area. Then the pressure drop on air side can be obtained as follows [2]:

$$\Delta p_a = \frac{G_a^2}{2\rho_i}\left[f_a \frac{A}{A_{min}} \rho_{a,i}\left(\frac{1}{\rho_a}\right)_m + \left(1 + \sigma^2\right)\left(\frac{\rho_{a,i}}{\rho_{a,o}} - 1\right)\right],$$

$$\text{s.t.} \quad \left(\frac{1}{\rho_a}\right)_m \neq \frac{1}{\rho_{a,m}} \quad \text{and} \quad \left(\frac{1}{\rho_a}\right)_m = \frac{1}{2}\left(\frac{1}{\rho_i} + \frac{1}{\rho_o}\right). \tag{37}$$

In the above equation, σ is the ratio of A_{min} to A. Finally, the pressure drop on the water side could be found by the following equation,

$$\Delta P_w = \frac{f_w \rho_w \vartheta_w^2 W}{2 d_i}. \quad (38)$$

3 OBJECTIVE FUNCTIONS AND CONSTRAINTS

Total weight and total annual cost are considered objective functions. Total weight includes weight of fins and weight of tubes,

$$TW = A_f \rho_f t_f + \left(\frac{\pi}{4}\right) N_t \rho_t W \left(d_O^2 - d_i^2\right). \quad (39)$$

Furthermore, total annual cost consists of investment cost and operating cost which are given as:

$$TAC = C_{in} + C_{OP}, \quad (40)$$

$$C_{in} = C_A A^p, \quad (41)$$

$$C_{op} = \left(K_{el} \tau \frac{\Delta P V_t}{\eta}\right)_a + \left(K_{el} \tau \frac{\Delta P V_t}{\eta}\right)_w. \quad (42)$$

The subsequent set of constraints is applied to the mentioned objective functions:

$$\Delta P_a < \Delta P_{a,\max}, \quad (43)$$

$$\Delta P_w < \Delta P_{w,\max}, \quad (44)$$

$$1 < \frac{A}{A_h} < 1.2, \quad (45)$$

$$\frac{W}{d_o} \geq 60, \quad (46)$$

$$300 < Re_a < 2 \times 10^4, \quad (47)$$

$$2300 < Re_w < 2 \times 10^6, \quad (48)$$

where, Re_a and Re_w are Reynolds numbers based on d_c and d_h, respectively. The maximum allowable pressure drops on the air side and water side, respectively, are denoted by $\Delta P_{a,\max}$, and $\Delta P_{w,\max}$.

4 DESIGN METHOD AND PARAMETERS

The steps involved in heat exchanger design based on the LMTD method using a trial-and-error process are as follows [18]:

1. Calculate the outlet temperature according to the heat transfer rate (heat duty) and operating parameters using the steady flow energy equation.
2. Look up the correction factor F_c and calculate LMTD; Eq. (28).
3. Select the size and arrangement of tubes and fins, and calculate the heat transfer area A_{first}; Eq. (5).
4. Calculate the convective heat transfer coefficients of the two sides and then, the overall heat transfer coefficient U; Eqs. (15), (19), and (21).
5. Determine the Calculated heat transfer area A_{cal}; Eq. (20).
6. Compare A_{cal} with A_{first}. If $A_{cal} > A_{first}$, then go back to step 3, until $1 < A_{first}/A_{cal} < 1.2$.
7. Calculate pressure drops and Reynolds numbers on both sides; Eqs. (43), (44), (47), and (48). If they are larger than the allowable pressure drops or are not in valid ranges of Reynolds numbers, then adjust the size and arrangement of tubes and fins until they satisfy specified allowable pressure drops, Reynolds numbers, and step 6.
8. Calculate objective function.

Note that complex factors exist here without consideration and this issue is covered by allowing an additional area of up to 20 %.

The outside tube diameter (d_o), transverse pitch (P_t), longitudinal pitch (P_l), fin pitch (F_p), number of tube rows (N), height of shape (H), and width of shape (W) are assumed as seven design parameters. These parameters and the range of their variations are listed in Table 1 [8]. Shape length, L, is not considered an independent variable, because it can be directly obtained from N and P_l.

Constructional parameters except for the number of tube rows are considered continuous for optimization purposes, however, they are available in discrete quantities. If the precision of design parameters is set to 0.01 (N excluded, which takes values 2, 3, 4, 5, and 6), there are 600, 1000, 1900, 750, 5, 350, and 200 choices for the above tabled variables and therefore $600 \times 1000 \times 1900 \times 750 \times 5 \times 350 \times 200 \approx 10^{17}$ trial-and-error efforts are needed to find the optimal design which is impossible. In the next section, first DE is explained, then we implement DELC and JDELC algorithms instead of a trial-and-error method to attain minimum objective functions in the feasible design space.

Table 1. The upper and lower bounds of design variables

Design variable	Search range
Outside tube diameter, [mm]	7 to 13
Transverse pitch, [mm]	20.5 to 30.5
Longitudinal pitch, [mm]	13 to 32
Fin pitch, [mm]	1 to 8.5
Number of tube rows	2 to 6
Height of shape, [m]	4.5 to 8
Width of shape, [m]	3 to 5

5 DIFFERENTIAL EVOLUTION ALGORITHM

A heuristic called an evolutionary algorithm (EA) was first inspired by biological evolution and employs mechanisms such as mutation, recombination, and selection. In other words, EA evolves an initial population after several generations. Therefore, the use of these algorithms has become popular in solving many problems, including engineering optimizations. In an optimization problem, the candidate vectors represent the individuals of a population.

DE is a simple, yet powerful algorithm proposed by Price et al. [21] and as a metaheuristic seeks to evolve an initial population toward the optimal solutions by iteratively improving them. This algorithm makes a few assumptions about the problem and can quickly reach the best solutions.

5.1 Standard DE

The DE in its standard form has three main parameters: population size NP, mutation factor F, and crossover rate CR. Attaining better solutions and convergence completely depends on the setting of these parameters. To adjust them, a few authors have suggested as following: Price et al. [21] proposed the setting $NP = 10n$, where, n is the number of design parameters, $F \in [0.5, 1]$, and $CR \in [0.8, 1]$. According to Rönkkönen et al. [22], a reasonable choice for population size is between $2n$ and $40n$, $F \in (0.4, 0.95]$, and $CR \in (0, 0.2)$ or $CR \in (0.9, 1)$ for separable and non-separable objective functions, respectively. Note that here objective functions are non-separable. Zielinski et al. [23] reported that, in many cases, the best results are obtained with the setting of $F \geq 0.6$ and $CR \geq 0.6$.

The standard DE includes four principal operations during an optimization problem: 1) initialization 2) mutation 3) crossover 4) selection. The general structure of the algorithm is shown in Fig. 2.

5.1.1 Initialization

In a problem with n design variable, each candidate vector is defined as $X = (x_1, x_1, \ldots, x_n)$. The purpose is to optimize objective function

$f(X)$. In the beginning, an initial population is generated including vectors as many as NP. Each member of the initial population is generated from Eq. (49). As a result, the initial population is an NP by n matrix.

$$x_{i,j} = x_{j(\min)} + rand(0,1) \times \left(x_{j(\max)} - x_{j(\min)}\right), \quad i = 1,2,\ldots,NP \quad \text{and} \quad j = 1,2,\ldots,n, \tag{49}$$

where, $x_{j(\max)}$ and $x_{j(\min)}$ are the maximum and minimum values of each design variable, respectively. Furthermore, $rand(0,1)$ is a uniformly distributed random number between 0 and 1.

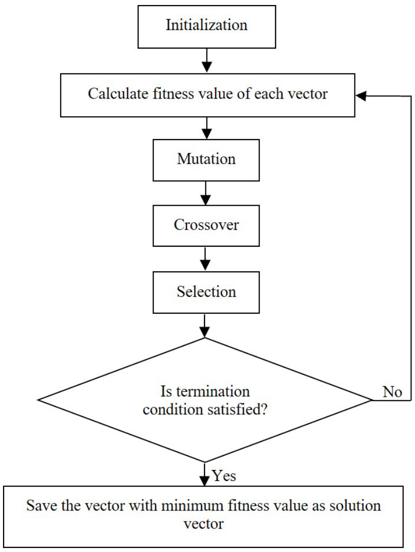

Fig. 2. Flowchart of standard DE algorithm

5.1.2 Mutation

In this step, a noisy population (donor vectors) is produced from the initial population as follows: for each vector from the current population, i^{th}, the mutated vector is obtained by combining three randomly selected vectors according to the formulation below:

$$\mathbf{M}_i = \left(m_{i,1},\ldots,m_{i,n}\right) = \mathbf{X}_c + F \times \left(\mathbf{X}_a - \mathbf{X}_b\right), \tag{50}$$

where, $\mathbf{X}_a$, $\mathbf{X}_b$, and $\mathbf{X}_c$ are three random vectors in the current population between 1 and NP except i^{th}. The mutation factor, F, is a positive real number that controls the rate at which the population evolves. F has no upper bound, however effective values are rarely larger than 1 [21]. This mutation step is replicated for all original vectors of the current population to produce new population members that would improve the search space. This strategy, named DE/rand/1, is the most popular and simplest DE variant, which uses one difference as a perturbation of the base vector. There are many other variants of the mutation mechanism that have been subsequently proposed by Das et al. [10] and Price et al. [21], such as DE/rand/2, DE/best/1, DE/best/2, etc. [24].

5.1.3 Crossover

After mutation, the i^{th} original vector from the current population is recombined with the corresponding vector from the mutated population to produce the trial vector $\mathbf{U}_i = (u_{i,1}, \ldots, u_{i,n})$. Each element of the trial vector is determined based on the following equation:

$$u_{i,j} = \begin{cases} m_{i,j} & \text{if } rand(0,1) < CR \text{ or } j = R \\ x_{i,j} & \text{otherwise} \end{cases}, \tag{51}$$

where CR is between 0 and 1 which represents the probability of selecting a trial vector from the original vector and mutated vector, and R is a random integer number between 1 and n.

5.1.4 Selection

As the last step, just one of the vectors, $\mathbf{X}_i$ (original) and $\mathbf{U}_i$ (crossed) can survive. This selection is done based on the type of problem as follows:

1. for an unconstrained problem, objective function values of the two above vectors are the comparison criteria. If the goal is a minimization problem, the vector with a lower objective function value will be selected, and vice versa. Eq. (52) represents the selection step due to the minimization of an objective function. The following process is repeated for a certain number of generations or until convergence criteria are satisfied.

$$\mathbf{X}_i^{t+1} = \begin{cases} \mathbf{U}_i^t & \text{if} \quad f\left(\mathbf{U}_i^t\right) < f\left(\mathbf{X}_i^t\right) \\ \mathbf{X}_i^t & \text{otherwise} \end{cases}. \tag{52}$$

2. If the problem is constrained, like the present case, in addition to checking the objective function, the constraints' fitness should also be checked.

In the next section, we apply α-level comparison to handle the optimization problem constraints.

5.2 Differential Evolution with Level Comparison

The canonical versions of EAs, including DE, lack a mechanism to bias the search to the most feasible area since they were not designed inherently to solve constrained optimization problems [25]. Hence, this has triggered a significant amount of investigation, and during the last years, many different methods for incorporating constraints into the fitness function of an EA have been proposed [26]. Practically, adjusting control parameters such as F and CR and coupling them with suitable and effective constraint-handling strategies can considerably enhance the search capability of DE algorithms. Differential evolution with level comparison (DELC) performs initialization, mutation, and crossover operations similar to standard DE, but besides objective function values, a satisfaction level for the constraints is considered, which indicates how well a search point (candidate vector) satisfies the constraints. In other words, this method quantifies the constraint violation [27].

Below, $f(\mathbf{X})$ is assumed to be a general function that should be minimized by the inequality constraints set $g_k(\mathbf{X})$ with $k = 1,\ldots,p$, and equality constraints set $h_s(\mathbf{X})$ with $s = 1,\ldots,q$.

$$\min_X f\left(\mathbf{X}\right) \quad \text{s.t.} \quad g_k\left(\mathbf{X}\right) \le 0; \quad k = 1,2,\ldots,p; \quad h_s\left(\mathbf{X}\right) = 0; \quad s = 1,2,\ldots,q. \tag{53}$$

From the first generation ($t=1$) to the end ($t=Gen_{\max}$), the selection between each original vector ($\mathbf{X}_i$) and its trial ($\mathbf{U}_i$) from the current population, will be done regarding DELC. Also, f_1 and f_2 are the objective function values of the mentioned vectors, respectively, and μ_1 and μ_2 are their related satisfaction levels. For instance, the resulting satisfaction level of vector $\mathbf{X}_i$ is determined by,

$$\mu_1 = \mu\left(\mathbf{X}_i\right) = \min_{k,s}\left\{\mu_{g_k}\left(\mathbf{X}_i\right), \mu_{h_s}\left(\mathbf{X}_i\right)\right\}, \tag{54}$$

where all constraints are calculated from piecewise linear functions as follows:

$$\mu_{g_k}\left(\mathbf{X}_i\right) = \begin{cases} 1 & \text{if} \quad g_k\left(\mathbf{X}_i\right) \le 0 \\ 1 - \dfrac{g_k\left(\mathbf{X}_i\right)}{b_k} & \text{if} \quad 0 \le g_k\left(\mathbf{X}_i\right) \le b_k \\ 0 & \text{otherwise} \end{cases}, \tag{55}$$

$$\mu_{h_s}\left(\mathbf{X}_i\right)=\begin{cases}1-\dfrac{\left|\mathbf{h}_s\left(\mathbf{X}_i\right)\right|}{b_s} & \text{if} \quad \left|h_s\left(\mathbf{X}_i\right)\right| \le b_s \\ 0 & \text{otherwise}\end{cases}, \tag{56}$$

where b_k and b_s are two positive numbers. In this study, the median values of the constraint violations in the initial population are employed and these parameters are updated after each generation.

Here, the selection between two sets of ($f(\mathbf{X}_i)$, $\mu(\mathbf{X}_i)$) and ($f(\mathbf{U}_i)$, $\mu(\mathbf{U}_i)$) based on DELC with α satisfaction level is according to:

$$\mathbf{X}_i^{t+1}=\begin{cases}\mathbf{U}_i^t & \left(f\left(\mathbf{U}_i^t\right),\mu\left(\mathbf{U}_i^t\right)\right)\le_\alpha\left(f\left(\mathbf{X}_i^t\right),\mu\left(\mathbf{X}_i^t\right)\right) \\ \mathbf{X}_i^t & \text{else}\end{cases}. \tag{57}$$

The α-level comparison $<\alpha$ and $\le\alpha$ between ($f(\mathbf{X}_i)$, $\mu(\mathbf{X}_i)$) = (f_1, μ_1) and ($f(\mathbf{U}_i)$, $\mu(\mathbf{U}_i)$) = (f_2, μ_2) are defined in this way:

$$\left(f_1,\mu_1\right)\le_\alpha\left(f_2,\mu_2\right)\Leftrightarrow\begin{cases}f_1\le f_2 & & \mu_1,\mu_2\ge\alpha \\ f_1\le f_2 & \text{if} & \mu_1=\mu_2 \\ \mu_1\ge\mu_2 & & \text{otherwise}\end{cases}, \tag{58}$$

It means that due to $\le\alpha$ comparison, (f_1, μ_1) is a better individual compared to (f_2, μ_2) when $f_1 \le f_2$ (in case of μ_1, $\mu_2 \ge \alpha$ or $\mu_1 = \mu_2$) or $\mu_1 \ge \mu_2$. Similar consequences can be pointed for $<\alpha$ comparison. Fig. 3 depicts the detailed implementation of the DELC algorithm. For those problems subjected to strong equality constraints, the α-level should be controlled to obtain high quality results. However, in this study, the α-level does not need to be controlled and like many constrained problems, can be solved when α is constantly 1 [27].

5.3 JDE

A standard DE algorithm contains a set of parameters that are remained constant throughout the optimization process. In order to achieve optimal performance, the tuning of these parameters for each optimization problem is necessary. Some researchers claim that manually setting the DE inputs is not too difficult [21]. However, some argue that this process may be effortful, especially for certain optimization problems [28]. The setting of the control parameters greatly affects the efficiency, effectiveness, and robustness of the DE algorithm. Hence, best parameter selection is a problem-specific question, because some may work well for some problems but not for others [29]. JDE has self-adaptive control parameter settings and shows acceptable performance in benchmark problems. JDE operates in such a way that uses a self-adaptive approach to adjust F and CR parameters for the best optimization results. The control parameters for JDE algorithm are:

$$F_i^{t+1}=\begin{cases}F_l+rand_1 F_u, & \text{if} \quad rand_2<\tau_1 \\ F_i^t, & \text{otherwise}\end{cases}, \tag{60}$$

$$CR_i^{t+1}=\begin{cases}rand_3, & \text{if} \quad rand_4<\tau_2 \\ CR_i^t, & \text{otherwise}\end{cases}. \tag{61}$$

$rand_j$ with $j \in \{1,2,3,4\}$ are uniformly distributed random numbers between 0 and 1 and τ_1 and τ_2 represent probabilities to set factors F and CR where $\tau_1=\tau_2=0.1$ is recommended, while $F_l=0.1$ and $F_u=0.9$, therefore the new range for F value will be [0.1, 1] [30].

As well as DELC, we use JDE with level comparison (JDELC) to obtain optimal structural parameters associated with an FTHE. Note that JDELC has a similar procedure to Fig. 3, except that it does not need to guess good values of F and CR in the initialization step and it has a self-adaption nature. The task of thermal design and optimization by DELC and JDELC algorithms is conducted in the Fortran programming language.

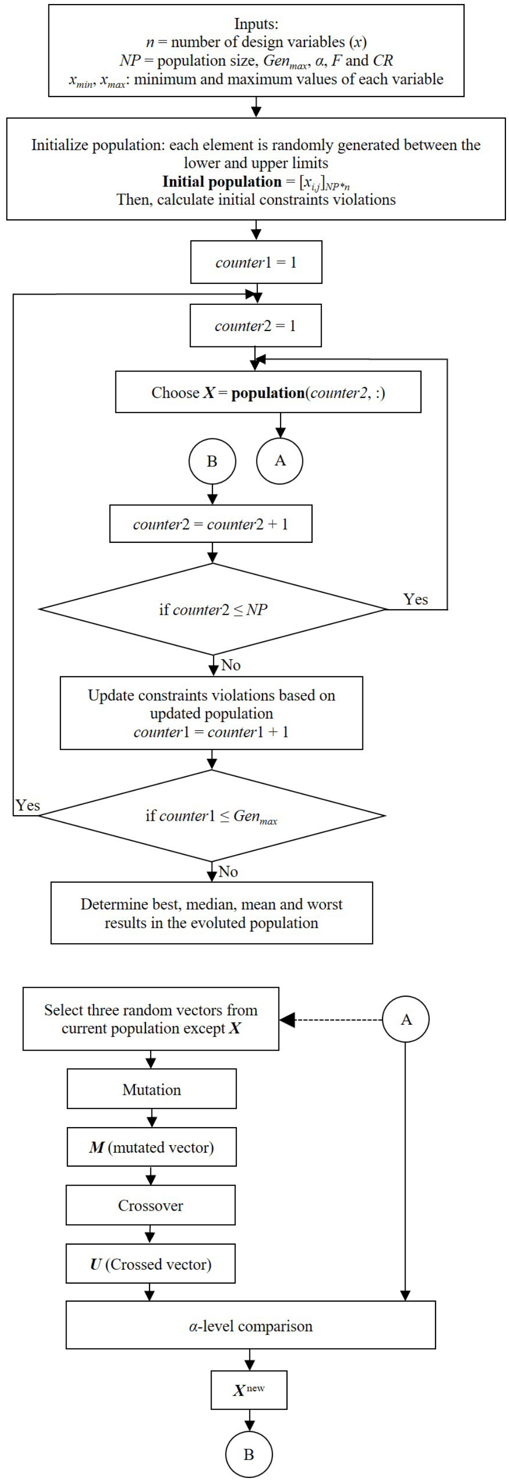

Fig. 3. Flowchart of DELC

6 A CASE STUDY AND RESULTS

To demonstrate the described procedure, a case study is considered and the effectiveness of the proposed algorithm is assessed by analyzing an application example that was earlier investigated by GA [8] and HTS [9]. The model of FTHE is cross-flow and both fluids are unmixed. The material of the tubes is stainless steel with a thermal conductivity of 15 W/(m·K) and a density of 7820 kg/m^3, while the fin material is aluminum with a thermal conductivity of

170 W/(m·K) and a density of 2790 kg/m³. Tables 2 and 3 show operating conditions and cost function constants, respectively.

Table 2. Operating parameters

Variable	Water side	Air side
Flow rate, [kg/s]	39.2	58.2
Inlet temperature, [°C]	20	104
Outlet temperature, [°C]		51
Inlet pressure, [kPa]	174.5	174.5
Allowable pressure drop, [Pa]	5200	5200
Heat duty, [kW]	3115	3115

Table 3. Economic constants

Variable	Value	Variable	Value
Cost per unit area, [$/m²]	100	Electricity price, [$/MWh]	30
Exponent for area	0.6	Pump efficiency	0.5
Hour of operation, [h/year]	6500		

For consistent comparison with previous works, air side, and water side allowable pressure drops are considered as 30 Pa and 4500 Pa, respectively. Also, the thermophysical properties of the fluids have been shown in Table 4. The subscript *t, m* returns to the mean temperature value.

Table 4. Thermophysical properties

Fluid	Air	Water
$T_m = (T_1+T_2)/2$, [°C]	77.5	29.5
ρ_i, [kg/m³]	1.612	-
ρ_o, [kg/m³]	1.875	-
$\rho_{t,m}$, [kg/m³]	1.734	995.8
$\rho_{ave} = (\rho_i+\rho_o)/2$, [kg/m³]	1.7435	-
$\mu_{t,m}$, [Pa·s]	0.00002085	0.0008059
$Cp_{t,m}$, [J/(kgK)]	1008	4180
$Pr_{t,m}$	0.7162	5.489
$k_{t,m}$, [W/(mK)]	-	0.6137
$\Delta T_1 = T_{h,i} - T_{c,o} = 104 - 39 = 65$ [°C]		
$\Delta T_2 = T_{h,o} - T_{c,i} = 51 - 20 = 31$ [°C]		
$\Delta T_{lm} = (\Delta T_1 - \Delta T_2) / (\ln (\Delta T_1/ \Delta T_2)) = 45.916$ [°C]		
$F_c = 0.946$		

6.1 Minimum Weight Optimization

Table 5, reports the statistical results for total weight minimization, including the best, median, mean, worst, and SD. The optimum results are marked with boldface.

Table 5. Algorithms' statistical results for total weight optimization

$G_{max} = 500$, $NP = 70$, and $\alpha = 1$						
	F	Best	Median	Mean	Worst	SD
DELC $CR = 0.9$	0.2	1080.00	1206.5	1206.5	1464.11	1.27e2
	0.4	**1013.17**	**1013.17**	1014.97	1041.77	5.9855
	0.6	**1013.17**	**1013.17**	**1013.17**	**1013.17**	**1.16e-16**
	0.8	**1013.17**	1015.02	1015.40	1019.14	1.5978
	1	**1013.17**	1014.62	1017.11	1039.78	5.9981
	1.2	1026.69	1055.82	1056.01	1089.65	16.668
JDELC: $\tau_1 = \tau_2 = 0.1$, $F_l = 0.1$, $F_u = 0.9$	F (Eq. (60)) CR (Eq. (61))	1013.17	1013.17	1013.31	1016.5	0.665

Table 6. Design results for minimum total weight consideration compared to GA [8] and HTS [9]

	GA	HTS	DE
Outside diameter, [mm]	12.63	11.9	10.72
Transverse pitch, [mm]	28.94	30.8	20.5
Longitudinal pitch, [mm]	27.26	30.7	14.89
Fin pitch, [mm]	1.23	1.2	1
Height of shape, [m]	7.29	7.79	8
Width of shape, [m]	4.08	3	3.39
Length of shape, [m]	0.0545	0.0614	0.0298
Number of tubes	502	504	779
Number of fins	3318	2501	3391
Number of tube rows	2	2	2
Fin thickness, [mm]	0.12	0.12	0.12
Volume, [m³]	1.62	1.43	0.81
Heat transfer area, [m²]	2294.48	2165.3	1222.59
Pressure drop on air side, [Pa]	30	30	30
Pressure drop on water side, [Pa]	4464	4495.1	4471.96
Total annual cost, [$/year]	10873.7	10523	7580.1
Weight of tubes, [kg]	584.66	406.45	630.61
Weight of fins, [kg]	750.42	711.65	383.12
Total weight, [kg]	1335.08	1118.1	1013.73

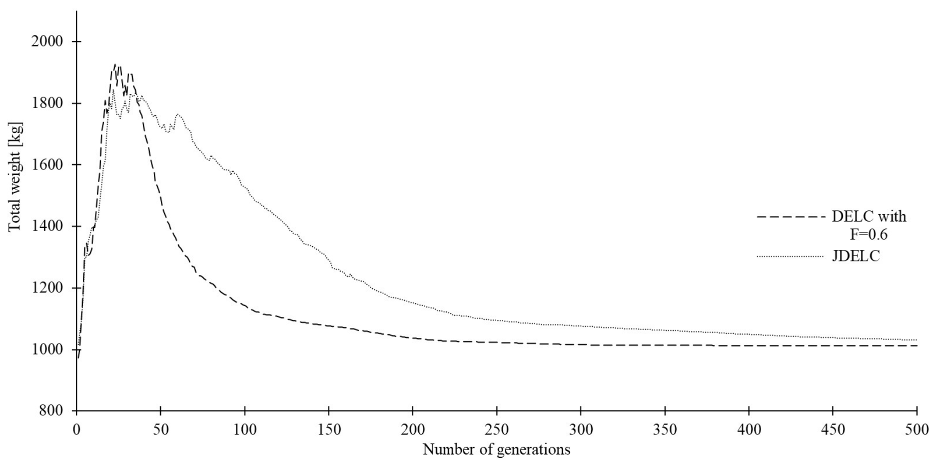

Fig. 4. Algorithms' convergence performance for total weight minimization

From the results provided in Table 5, it is observed that DELC with F = 0.4, 0.6, 0.8, and 1 and JDELC obtain the finest solution at least once, but only DELC with F = 0.6 and JDELC have a minimum of the median, mean, and worst. Moreover, the SD of these two cases is the lowest. So, these concluded as the best schemes. Fig. 4 demonstrates the evolution process related to total weight optimization. As seen from Fig. 4, DELC with F = 0.6 converges considerably earlier. Also, after about 150 generations, there are very slight variations in individuals, and finally, an acceptable level of optimal weight is reached. As a result, DELC with F = 0.6 provides better performance than others and has been chosen as the best manner.

Table 6 shows DELC algorithm's optimum solution for minimum total weight and those obtained by the GA and HTS algorithms previously. When compared to the results of the HTS algorithm, which were reported before as the best in terms of total weight, a significant decrease (33.4 %) in transverse pitch leads obviously to an enormous increase (54.6 %) in the number of tubes and, consequently, the weight of tubes increases by 55.2 %. The number of fins increases (35.6 %) due to the rise in width of shape (13 %) and decrease in fin pitch (16.7 %). Despite an increase in the number of fins, a significant decrease in the length of shape (51.5 %) besides an increase in the number of tubes (As confirmed by Eqs. (5) and (7), resulted in a noticeable decrease (43.5 %) in the heat transfer area, and so weight of fins decreases by 46.2 %.

Overall, the combined effect of changes in the weight of tubes and fins results in a reduction of total weight of about 24.07 % and 9.33 % employing DE as compared to GA and HTS, respectively.

6.2 Minimum Cost Optimization

Like the first objective function, shown in Table 5, outcomes for total annual cost optimization are calculated and listed in Table 7. Similarly, the optimal cases are mentioned in boldface.

From the results presented in Table 7, five items achieve the elite solution, but the median, mean, and worst are minimum for DELC only with F = 0.6 and F = 0.8 besides the SD of both choices is too small. Again, DELC with F = 0.6 has a higher speed of convergence compared to the other as illustrated in Fig. 5. Furthermore, the number of generations needed to gain a good approximation is about 150. It may make sense that convergence curves have considerable overshoot in both weight and cost optimizations, as shown in Figs. 4 and 5, however, it has been observed that the behavior is significantly influenced by design variable N. The optimum solution found by the DELC algorithm for minimum total annual cost is gathered in Table 8.

Table 7. Algorithms' statistical results for total annual cost optimization

G_{max} = 500, NP = 70, and α = 1						
	F	Best	Median	Mean	Worst	SD
DELC CR = 0.9	0.2	6778.76	7377.44	7491.69	8605.47	508.364
	0.4	**6286.38**	6287.96	6484.78	7002.65	261.387
	0.6	**6286.38**	**6286.38**	**6286.38**	**6286.38**	**1.85e-12**
	0.8	**6286.38**	**6286.38**	6286.39	6286.68	**0.05968**
	1	**6286.38**	**6286.38**	6288.43	6298.81	3.86347
	1.2	6333.65	6403.27	6396.35	6462.06	37.4456
JDELC: $\tau_1 = \tau_2$ = 0.1, F_l = 0.1, F_u = 0.9	F (Eq. (60)) CR (Eq. (61))	**6286.38**	**6286.38**	6286.58	6291.36	0.996

Table 8. Design results for minimum total annual cost consideration compared to GA [8] and HTS [9]

	GA	HTS	DE
Outside diameter, [mm]	13	13	13
Transverse pitch, [mm]	21.78	20.4	20.5
Longitudinal pitch, [mm]	27.26	24.6	16.89
Fin pitch, [mm]	2.87	2.37	1.5
Height of shape, [m]	7.59	5.8	5.54
Width of shape, [m]	4.95	5	5
Length of shape, [m]	0.0545	0.0492	0.03378
Number of tubes	454	567	539
Number of fins	2645	2111	3335
Number of tube rows	2	2	2
Fin thickness, [mm]	0.12	0.12	0.12
Volume, [m^3]	2.05	1.43	0.9357
Heat transfer area, [m^2]	1114.45	989.37	876.73
Pressure drop on air side, [Pa]	30	29.14	30
Pressure drop on water side, [Pa]	2654	1856.9	4151.17
Total weight, [kg]	1388.52	1137.46	1054.13
Capital cost, [$/year]	6733.4	6269.2	5830.69
Operating cost, [$/year]	689.1	483.6	457.97
Total annual cost, [$/year]	7422.5	6752.8	6288.66

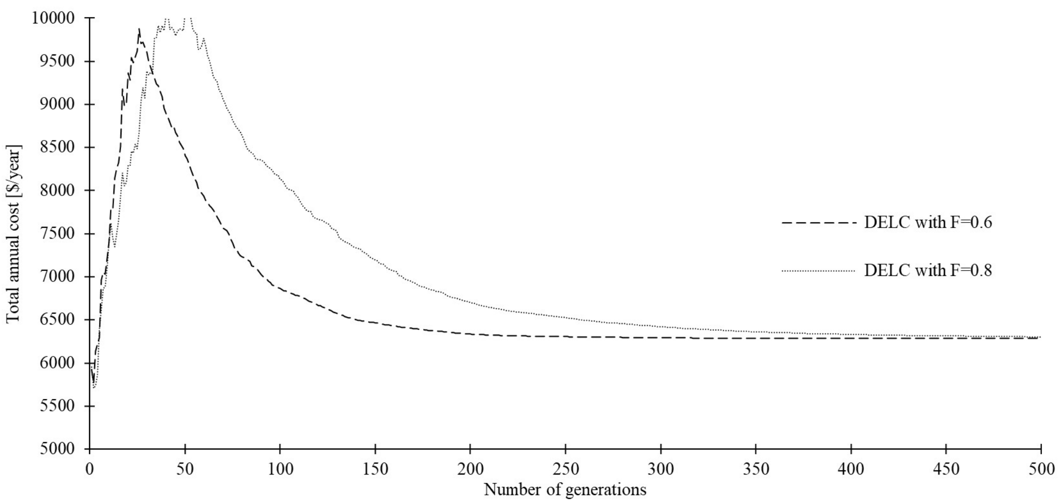

Fig. 5. Algorithms' convergence performance for total annual cost minimization

As before, when comparing the optimum solution obtained by the DELC method to HTS findings, as the best result for total annual cost, while the width of shape remains constant, a remarkable increase (58 %) in the number of fins occurred by a large decrease (36.7 %) in fin pitch. Despite an increase in the number of fins, a noticeable decrease (31.3 %) in the length of shape has resulted in a significant decrease (11.4 %) in the heat transfer area (As expected from Eqs. (5) and (7)) and a considerable decrease in capital cost by 7 %. Furthermore, an increase in transverse pitch and a decrease in height of shape reduce the number of tubes by 4.9 % and operating cost by 5.3 %. As a result, when compared to GA and HTS, the DELC algorithm saves 15.28 % and 6.87 % of the total annual cost, respectively. It is important to mention that the design variables are rounded in Tables 6 and 8 and the objective functions are calculated accordingly.

The achievements for both objective functions show that the DE algorithm with α-level constraint control, provides significant improvements in optimal designs by finding the desirable variables with satisfied constraints, compared to GA and HTS.

7 PARAMETRIC ANALYSIS

In this section, sensitivity analysis is used to determine how objective functions are affected based on changes in structural parameters and to indicate the feasible design space. For this purpose, each variable is changed within the predefined ranges, while others are kept constant at their optimum obtained by DE. Figs. 6 and 7 show the influence of variation of outside tube diameter, transverse pitch, longitudinal pitch, fin pitch, number of tube rows, height of shape, and width of shape on total weight. In these figures, only areas shown with symbols are feasible.

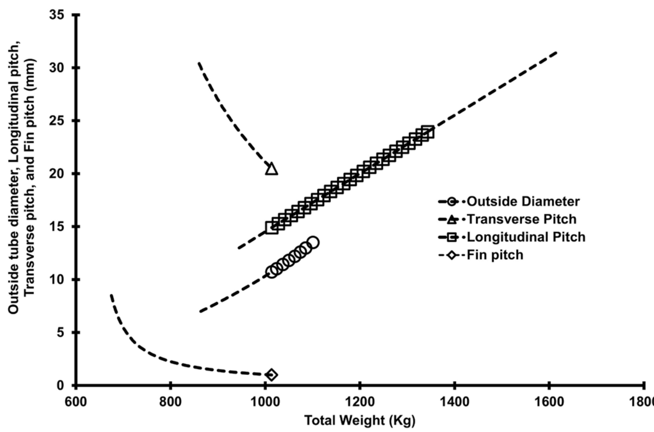

Fig. 6. Effect of outside tube diameter, transverse pitch, longitudinal pitch, and fin pitch on total weight

As seen from these figures, increases in the outside tube diameter, longitudinal pitch, number of tube rows, height of shape, and width of shape lead to a linear increment in the total weight of the heat exchanger, furthermore, as expected when transverse pitch and fin pitch increase, the mentioned objective function values decrease. Figures show that parametric optimization results agree with the solutions acquired by DE algorithm because total weight is optimum when transverse pitch and fin pitch are minimum and height of shape is maximum. Accordingly, the optimum solution occurs when there are two rows of tubes and the outside tube diameter, longitudinal pitch, and width of shape are equal to 10.72 mm, 14.89 mm, and 3.39 m, respectively. Moreover, the feasible space for the design parameters; outside tube diameter, longitudinal pitch, and width of shape is obtained in this way: 10.72 mm to 13.5 mm, 14.89 mm to 23.95 mm, and 3.39 mm to 3.41 m. Beyond this range, constraint violation happens. As a result of parametric analysis, 24.45 % of the solutions are practicable around the obtained optimal point. Similarly, Figs. 8 and 9 illustrate the variation of those parameters in the solution space for the total annual cost objective function.

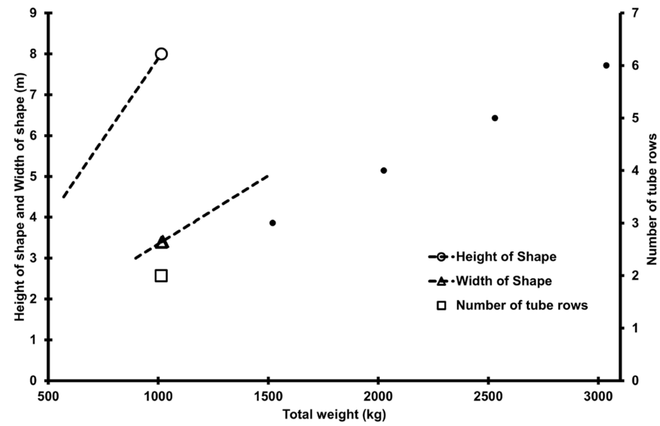

Fig. 7. Effect of height of shape, width of shape, and number of tube rows on total weight

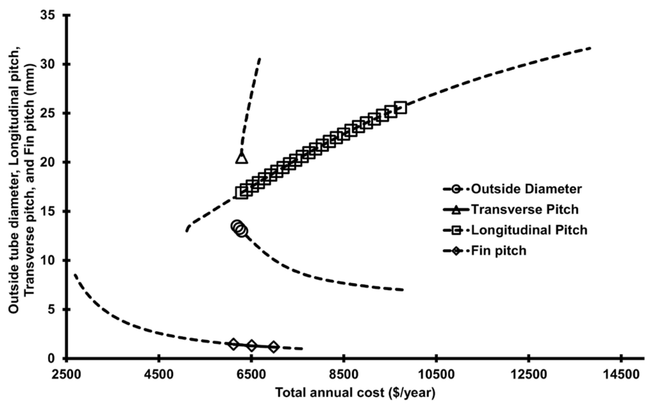

Fig. 8. Effect of outside tube diameter, transverse pitch, longitudinal pitch, and fin pitch on total annual cost

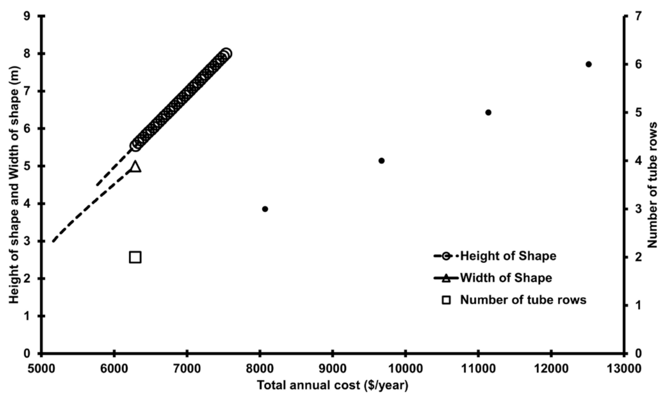

Fig. 9. Effect of height of shape, width of shape, and number of tube rows on total annual cost

The above figures indicate that an increase in the outside tube diameter and fin pitch leads to a decrease in the total annual cost of the heat exchanger, primarily due to the reduction in pressure drop, which subsequently lowers the operation cost. However, increases in transverse pitch, longitudinal pitch, number of tube rows, as well as the height and width of the shape, result in a higher total annual cost. This cost is optimal when the outside tube diameter, transverse pitch, and width of shape are at their maximum (13 mm), minimum (20.5 mm), and maximum (5 m), respectively. Also, the optimum solution is obtained where the longitudinal pitch, number of tube rows and height of shape are equal to 16.89 mm, 2 m and 5.54 m, respectively. In addition, as shown, those parameters are feasible for outside tube diameter, longitudinal pitch, fin pitch and height of shape which are within 13 to 13.5 mm, 16.89 mm to 25.57 mm, 1.17 mm to 1.5 mm, and 5.54 m to 8 m, respectively. It should be noted that an outside tube diameter between 7 mm and 13 mm is selected as the search range in the DE routine, but up to 13.5 mm is in the valid range [16], and used in the parametric analysis. A violation of the constraint occurs outside of these ranges. As a whole, 24.68 % of the space in total annual cost parametric analysis is applicable.

8 CONCLUSION

In this paper, the DE algorithm and JDE as a variant of standard DE are successfully implemented in the thermal design of a plain fin and tube heat exchanger based on the minimization of the total weight and total annual cost as two individual objective functions. For this purpose, the α-level constraint-handling method is incorporated into the global search capability of DE. Improvements in the results are observed for both objective functions with those reported by GA and HTS approaches previously. Finally, 24.07 % and 9.33 % reduction in total weight, and 15.28 % and 6.87 % in total annual cost are achieved using the DELC algorithm as compared to the two mentioned procedures. Consequently, applying the DELC algorithm to optimize FTHEs could give better results than the others. The performance of the gas side in the present FTHE may be improved by replacing continuous plain fins with high-performance fins, i.e., strip fins, slit fins, and louver fins. Furthermore, this study can be extended to the optimization of other types of heat exchangers for different goals in future work.

NOMENCLATURES

A	initial heat transfer area, [m²]
A_h	heat transfer area based on overall heat transfer coefficient, [m^2]
A_i	water side heat transfer area, [m^2]
$A_{\min}$	minimum free flow area, [m^2]
A_o	air side heat transfer area, [m^2]
CR	crossover rate,
C_A	price per unit area, [$\$/m^2$]
C_{in}	annual cost of investment, [$/year]
C_{op}	annual cost of operation, [$/year]
C_p	specific heat at constant pressure, [J/(kgK)]
d_c	fin collar outside diameter, [mm]
d_h	hydraulic diameter, [mm]
d_i	inside tube diameter, [mm]
d_o	outside tube diameter, [mm]
f	friction factor,
F	mutation factor,
F_c	correction factor,
F_p	fin pitch, [mm]
F_s	fin space, [mm]
H	height of shape, [m]
k	thermal conductivity, [W/(m^2K)]
N_f	number of fins per unit length,
NP	population size,
N_t	number of tubes,
Nu	Nusselt number,
m	fin parameter defined by Eq. (23),
n	number of design variables,
p	exponent of area,
P_l	longitudinal tube pitch, [mm]
Pr	Prandtl number,
P_t	transverse tube pitch, [mm]
R	radius of tube based on d_o, [mm]
$r_{f,eq}$	equivalent circular fin radius, [mm]
Re	Reynolds number based on d_h,
Re_{dc}	Reynolds number based on d_c,
R_{fi}	internal fouling resistance, [m^2K/W]
R_{fo}	external fouling resistance, [m^2K/W]
t_f	fin thickness, [mm]
TAC	total annual cost, [$/year]
TW	total weight, [kg]
U	overall heat transfer coefficient, [W/(m^2K)]
V	volumetric flow rate, [m^3/s]
W	width of shape, [m]
x	design variable,
$\mathbf{X}$	vector of design variables

Greek letters

η	pump and compressor efficiencies,
η_f	fin efficiency,
η_i	internal surface efficiency,
η_o	external surface efficiency,
υ	minimum flow velocity, [m/s]
μ	fluid dynamic viscosity, [Pa·s]
σ	contraction ratio of cross-sectional area,
ρ	density, [kg/m^3]
τ	hours of operation per year, [hours/year]
ΔP	pressure drop, [Pa]
ΔT_m	mean temperature difference, [K]
ΔT_{lm}	logarithmic mean temperature difference, [K]
ϕ	parameter defined by Eq. (24)

Subscripts

a	air side
c	cold side
f	fin
h	hot side
i	inlet
m	mean
min	minimum
max	maximum
o	outlet
t	tube
w	water side

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Uporaba diferencialnega evolucijskega algoritma za termodinamično snovanje in omejena optimizacija cevno orebrenega prenosnika toplote

Povzetek *Cevno orebreni prenosniki toplote (COPT) so vrsta kompaktnih prenosnikov toplote (KPT), ki je razširjena v aplikacijah prenosa toplote med plini in tekočinami. V pričujoči študiji se za optimizacijo COPT učinkovito uporabljata algoritem diferencialne evolucije (DE) in njegova različica JDE s tehniko obvladovanja omejitev na ravni α. Za ciljni funkciji sta bili izbrani skupna teža in letni strošek obratovanja prenosnika toplote. Zajetih je bilo sedem konstrukcijskih spremenljivk: zunanji premer cevi, prečni razmik, vzdolžni razmik, razmik reber, število vrst cevi, višina in širina oblike. Za analizo prenosa toplote pod enakimi pogoji, kot so masni pretok, vstopna in izstopna temperatura, toplotna obremenitev in druge toplotne lastnosti, se uporablja metoda srednje logaritemske temperaturne razlike. Za reševanje optimizacijskih problemov so bistveno primernejši metahevristični iskalni algoritmi. Pri obeh ciljnih funkcijah so se izboljšali rezultati v primerjavi z genetskim algoritmom (GA) in tako imenovanim algoritmom iskanja prenosa toplote. Parametrična analiza je potrdila, da sta vrednosti ciljnih funkcij minimalni pri najmanjši vrednosti prečnega razmika. Predlagana metoda je preprosta in v splošnem uporabna pri termodinamičnem snovanju in optimizaciji COPT in drugih vrst KPT za različne namene.*

Ključne besede *cevno orebreni prenosnik toplote, termodinamična zasnova, optimizacija z omejitvami, diferencialni evolucijski (DE) algoritem, skupna teža, skupni letni strošek*