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A Posteriori Multiobjective Self-Adaptive Multipopulation Jaya Algorithm for Optimization of Thermal Devices and Cycles

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ABSTRACT This paper presents the multiobjective optimization aspects of three thermal devices and two thermodynamic cycles. The thermal devices considered are two-stage thermoelectric cooler, heat pump, and a plate-fin heat exchanger. The thermodynamic cycles considered are transcritical CO_2 cycle and the irreversible Carnot power cycle. *A posteriori* is proposed, and it is applied for the multiobjective optimization of the selected thermal devices and cycles to obtain the sets of nondominated alternative solutions. The results of computational experiments obtained by the MO-SAMP Jaya algorithm are found to be better than those obtained by the latest reported optimization algorithms.

INDEX TERMS Carnot cycle, heat pump, Jaya algorithm, multiobjective optimization, plate-fin heat exchanger, thermoelectric cooler, transcritical cycle.

I. INTRODUCTION

Solving the complex optimization problems in the limited time is an indispensable issue in the field of engineering optimization. Due to the complexity of the problems, the conventional methods become tedious and time-consuming and these approaches do not guarantee the achievement of the optimal solution. Therefore, metaheuristic based computational methods (also called advanced optimization algorithms) are developed. These methods are capable of achieving the global or near global optimum solution with less information about the problems.

Some of the well-known advanced optimization algorithms are: genetic algorithm (GA) and its variants (real coded GA, parallel GA, hybrid interval GA, etc.), simulated annealing (SA) algorithm, tabu search (TS), ant colony optimization (ACO), particle swarm optimization (PSO) and its variants (e.g. niching PSO, culture-based PSO, aging theory inspired PSO, etc.), differential evolution (DE) and its variants (e.g. DE with multi-population ensemble, DE with self-adapting control parameter, DE with optimal external archive etc.), nondominated sorting genetic algorithm (NSGA) and its variants, etc.

In the last decade several metaheuristic algorithms are proposed. Some prominent algorithms are: artificial bee colony (ABC) algorithm, imperialist competitive algorithm (ICA), firefly algorithm (FFA), gravitational search algorithm (GSA), bat algorithm (BA), cuckoo search (CS), teaching-learning-based optimization (TLBO) algorithm, differential search algorithm, colliding bodies optimization algorithm, grey wolf optimization algorithm, ant lion optimization algorithm, cat swarm optimization algorithm, etc. [1]–[3].

The advanced optimization algorithms have their own merits but they require tuning of their specific parameters. For example, GA needs a proper setting of crossover probability, mutation probability, selection operator, etc.; NSGA needs crossover probability, mutation probability, SBX parameter, mutation parameter, etc.; SA algorithm needs initial annealing temperature and cooling schedule. PSO needs inertia weight and social and cognitive parameters. Similarly, ICA, DE and other algorithms (except TLBO algorithm) have respective specific parameters to be set for effective execution. These parameters are called algorithm-specific parameters and need to be controlled in addition to the common control parameters of number of iterations and population size. All population-based algorithms need to tune the common control parameters but the algorithm-specific parameters are specific to the particular algorithm and these are also to be tuned as mentioned above.

The performance of the optimization algorithms is much affected by the algorithm-specific parameters. Increase in the computational cost or tending towards the local optimal solution is caused by the improper tuning of these parameters. Hence, to overcome the problem of tuning of algorithm-specific parameters, TLBO algorithm was proposed which is an algorithm-specific parameter less algorithm [3], [4]. Keeping in the view of the good performance of the TLBO algorithm, another algorithm-specific parameter less algorithm has been recently proposed and it is named as Jaya algorithm [5].

The thermal system design process consists of many objecvtives based on the application requirements and these objectives are: heat transfer rate, cooling capacity, coefficient of performance, thermal resistance, pressure amplitude, effectiveness, pressure drop, etc. The total cost of the system should be minimized while achieving the desired objectives within the specified limits of the constraints. A number of design variables and objective functions are involved in the design optimization of a thermal system. Therefore, it would be beneficial to apply optimization techniques to individual components or intermediate systems than to a whole system. For example, in a thermal power plant, individual optimization of heat pump, heat pipe and cooling tower are computationally and mathematically simpler as compared to optimization of the entire system [6].

For the design optimization of thermal systems and devices some advanced optimization techniques have been applied such as GA, multiobjective GA (MOGA), PSO, ABC, differential evaluations (DE), Grenade explosion method (GEM), niched pareto genetic algorithm (NPGA) and teaching-learning-based optimization (TLBO) algorithm for the optimization of different objectives [7]. These algorithms have shown their excellent performance in a number of design optimization problems. However, these algorithms require algorithm-specific parameters (except TLBO algorithm) to be tuned.

Recently, an algorithm-specific parameter-less algorithm called Jaya algorithm has been developed [5]. The Jaya algorithm is simple in concept and is reported to give better results as compared to the other optimization algorithms. In this paper a posteriori multiobjective version of Jaya algorithm named as multiobjective self-adaptive muti-population Jaya algorithm is developed and this is applied for the design optimization of selected thermal devices and basic thermal cycles. The selected thermal devices include two-stage thermoelectric cooler (TEC), two-stage irreversible heat pump (HP), plate-fin heat exchanger (PFHE) and selected basic thermal cycles include transcritical cycle and irreversible Carnot power cycle. The key feature of MO-SAMP Jaya algorithm is that it can provide a set of nondominated solutions in a single simulation run.

The objectives of this research work are as follows:

a) To develop a posteriori multiobjective version of the self-adaptive multipopulation Jaya algorithm.
b) To apply the posteriori multiobjective version of the Jaya algorithm to the design optimization of selected thermal devices such TEC, two-stage irreversible HP, PFHE and two basic thermal cycles known as transcritical cycle and irreversible Carnot power cycle and to compare the results with those of the other advanced optimization algorithms.

The next section presents the details of working of MO SAMP-Jaya algorithm which is developed and used in this research papers for the design optimization of selected thermal devices and basic thermal cycles.

II. PROPOSED MO-SAMP JAYA ALGORITHM

In the Jaya algorithm, the candidate solutions in every iteration are updated in accordance with (1) [5]:

$$A'_{q,r,i} = A_{q,r,i} + r_1 * (A_{q,best,i} - |A_{q,r,i}|) - r_2 * (A_{q,worst,i} - |A_{q,r,i}|) \quad (1)$$

where, $A_{q,r,i}$ is the value of the q^{th} variable for the r^{th} candidate for the i^{th} iteration, and $\boldsymbol{A'_{q,r,i}}$ is the modified value of the same. $\boldsymbol{A_{q,best,i}}$ and $\boldsymbol{A_{q,worst,i}}$ is value of q^{th} variable corresponding to the best and worst solutions respectively in the entire population during the i^{th} iteration. The modified solutions will be accepted if found better than the previous solution(s) otherwise old solution(s) will be kept. For more details of working of the Jaya algorithm the readers may refer to [7]. The proposed MO-SAMP Jaya algorithm is a posteriori multiobjective optimization version of self-adaptive multi-population Jaya algorithm [8] which is a modified version of Jaya algorithm. The detailed working of MO-SAMP Jaya algorithm is shown in Fig. 1.

There are basically two approaches to solve a multiobjective optimization problem and these are: *a priori* approach and *a posteriori* approach. In *a priori* approach, multiobjective optimization problem is transformed into a single objective optimization problem by assigning an appropriate weight to each objective. This ultimately leads to a unique optimum solution. In the a priori approach, the preferences of the decision maker are asked and the best solution according to the given preferences is found. The preferences of the decision maker are in the form of weights assigned to the objective functions. The weights may be assigned through any method like direct assignment, eigenvector method [9], empty method, minimal information method, etc. Once the weights are decided by the decision maker, the multiple objectives are combined into a scalar objective via the weight vector. However, if the objective functions are simply weighted and added to produce a single fitness, the function with the largest range would dominate the evolution. A poor input value for the objective with the larger range makes the overall value much worse than a poor value for the objective with smaller range. To avoid this, all objective functions are normalized to have same range. For example, if $f_1(x)$ and $f_2(x)$ are the two objective functions to be minimized, then the combined objective function can be written as,

$$min\, f(x) = \{w_1 \left[\left(\frac{f_{1(x)}}{f_1^*} \right) \right] + w_2 \left[\left(\frac{f_{2(x)}}{f_2^*} \right) \right] \qquad (2)$$

where, $f(x)$ is the combined objective function and f_1^* is the minimum value of the objective function $f_1(x)$ when solved it independently without considering $f_2(x)$ (i.e. solving the multiobjective problem as a single objective problem and considering only $f_1(x)$ and ignoring $f_2(x)$). And f_2^* is the minimum value of the objective function $f_2(x)$ when solved it independently without considering $f_1(x)$ (i.e. solving the multiobjective problem as a single objective problem considering only $f_2(x)$ and ignoring $f_1(x)$). w_1 and w_2 are the weights assigned by the decision maker to the objective functions $f_1(x)$) and $f_2(x)$ respectively.

Suppose $f_1(x)$ and $f_2(x)$ are not of the same type (i.e. minimization or maximization) but one is a minimization function (say $f_1(x)$) and the other is a maximization function (say $f_2(x)$). In that case, (2) is written as (3) and f_2^* is the maximum value of the objective function $f_2(x)$ when solved it independently without considering $f_1(x)$.

$$min\, f(x) = \{w_1 \left[\left(\frac{f_{1(x)}}{f_1^*} \right) \right] - w_2 \left[\left(\frac{f_{2(x)}}{f_2^*} \right) \right] \} \qquad (3)$$

In general, the combined objective function can include any number of objectives and the summation of all weights is equal to 1. The solution obtained by this process depends largely on the weights assigned to the objective functions. This approach does not provide a set of Pareto points. Furthermore, in order to assign weights to each objective the process planner is required to precisely know the order of importance of each objective in advance which may be difficult when the scenario is volatile or involves uncertainty. This drawback of *a priori* approach is eliminated in *a posteriori* approach, wherein it is not required to assign the weights to the objective functions prior to the simulation run.

A posteriori approach provides multiple tradeoff (Pareto-optimal) solutions for a multiobjective optimization problem in a single simulation run. The designer or process planner can then select one solution from the set of Pareto-optimal solutions based on the requirement or order of importance of objectives. On the other hand, as *a priori* approach provides only a single solution at the end of one simulation run, in order to achieve multiple trade-off solutions using a priori approach the algorithm has to be run multiple times with different combination of weights. Thus, *a posteriori* approach is very suitable for solving multiobjective optimization problems wherein taking into account frequent change in customer desires is of paramount importance and determining the weights to be assigned to the objectives in advance is difficult. Evolutionary algorithms are popular approaches for generating the Pareto optimal solutions to a multiobjective optimization problem. Currently, most evolutionary multiobjective optimization algorithms apply Pareto-based ranking schemes [10]. Evolutionary algorithms such as the Nondominated Sorting Genetic Algorithm-II (NSGA-II) and Strength Pareto Evolutionary Algorithm 2 (SPEA-2) have become standard approaches. The main advantage of evolutionary algorithms, when applied to solve multiobjective optimization problems, is the fact that they typically generate sets of solutions, allowing computation of an approximation of the entire Pareto front. The main disadvantage of evolutionary algorithms is their lower speed and the Pareto optimality of the solutions cannot be guaranteed. It is only known that none of the generated solutions dominates the others. Furthermore, these algorithms require the tuning of respective algorithm-specific parameters.

In this paper MO-SAMP Jaya algorithm is proposed which does not have any algorithm-specific parameters to tune. The step by step working of MO-SAMP Jaya algorithms is defined as follows:

Step 1: Set the design variables (d), population size (P) and stopping condition.

Step 2: Calculate the value of fitness function for the initial populations.

Step 3: Group the entire population into m number of subpopulations based on the non dominance rank and crowding distance of solutions.

The solution with the highest rank (rank=1) is selected as the best solution. The solution with the lowest rank is selected as the worst solution. In case, there exists more than one solution with the same rank in a population or subpopulation then the solution with the highest value of crowding distance is selected as the best solution and vice versa. This ensures that the best solution is selected from the sparse region of the search space.

Step 4: Update solutions of each group as per (1).

Step 5: All the modified solutions of subpopulation are merged into single population.

Step 6: Initial/previous solutions and modified solution are merged into single population which is equals to 2*P populations.

Step 7: Nondominated sorting and crowding distance computation of the population is done and P best solutions are selected from 2*P solutions.

Step 8: Check for the improvement in rank 1 solution(s):

If Yes
    then m=m + 1;
Else ifm>1
    then m= m − 1;
End

Step 9: Check the stopping condition(s) reached.

If yes, then terminate the process and report the best optimum solution. Otherwise, go to Step 3 and follow the steps until the stopping condition is reached.

The readers may refer to [4] for detailed evaluation of nondominated sorting and calculation of crowding distance. The proposed MO-SAMP Jaya algorithm is used in this work for the design optimization of selected thermal devices and basic thermal cycles.

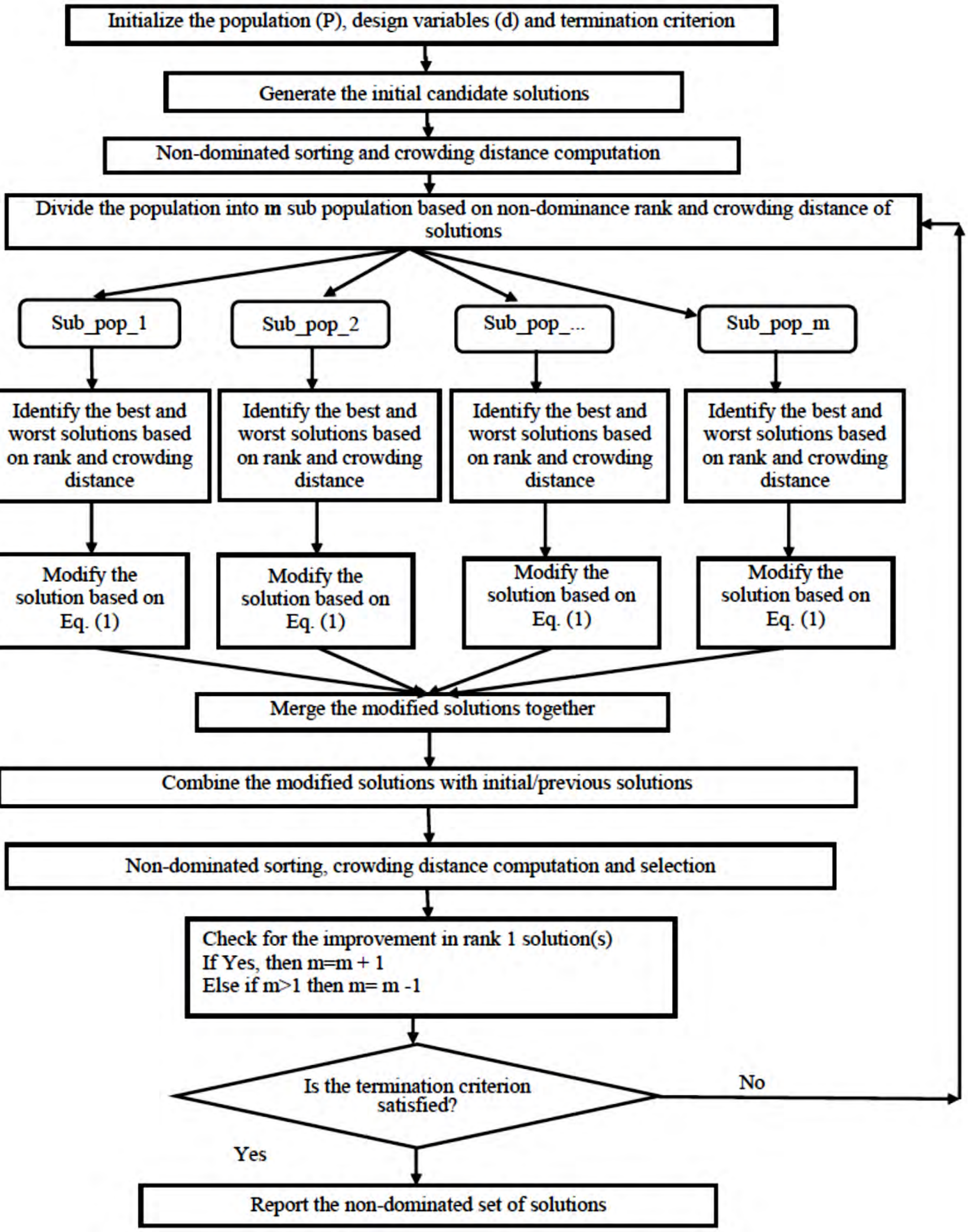

FIGURE 1. Flowchart of MO-SAMP Jaya algorithm.

The next section presents the precious research work carried out for the design optimization of selected thermal devices and basic thermal cycles.

III. LITERATURE REVIEW ON OPTIMIZATION OF SELECTED THERMAL DEVICES AND BASIC THERMAL CYCLES

A. THERMO-ELECTRIC COOLER

Due to the need of a steady, low temperature and eco-friendly operating environment for different applications the demand of thermoelectric coolers (TECs) has grown significantly. It is extensively used in various applications such as aerospace, military, medicine, and other electronic devices etc. However, the cooling capacity and coefficient of performance (COP) of TCEs are comparatively low as compared with traditional cooling devices. Therefore, the improvement in the performance of TECs is the most important issue in their applications [11], [12].

Single stage TEC can produce a maximum temperature difference of 70 K when its hot end is maintained at room

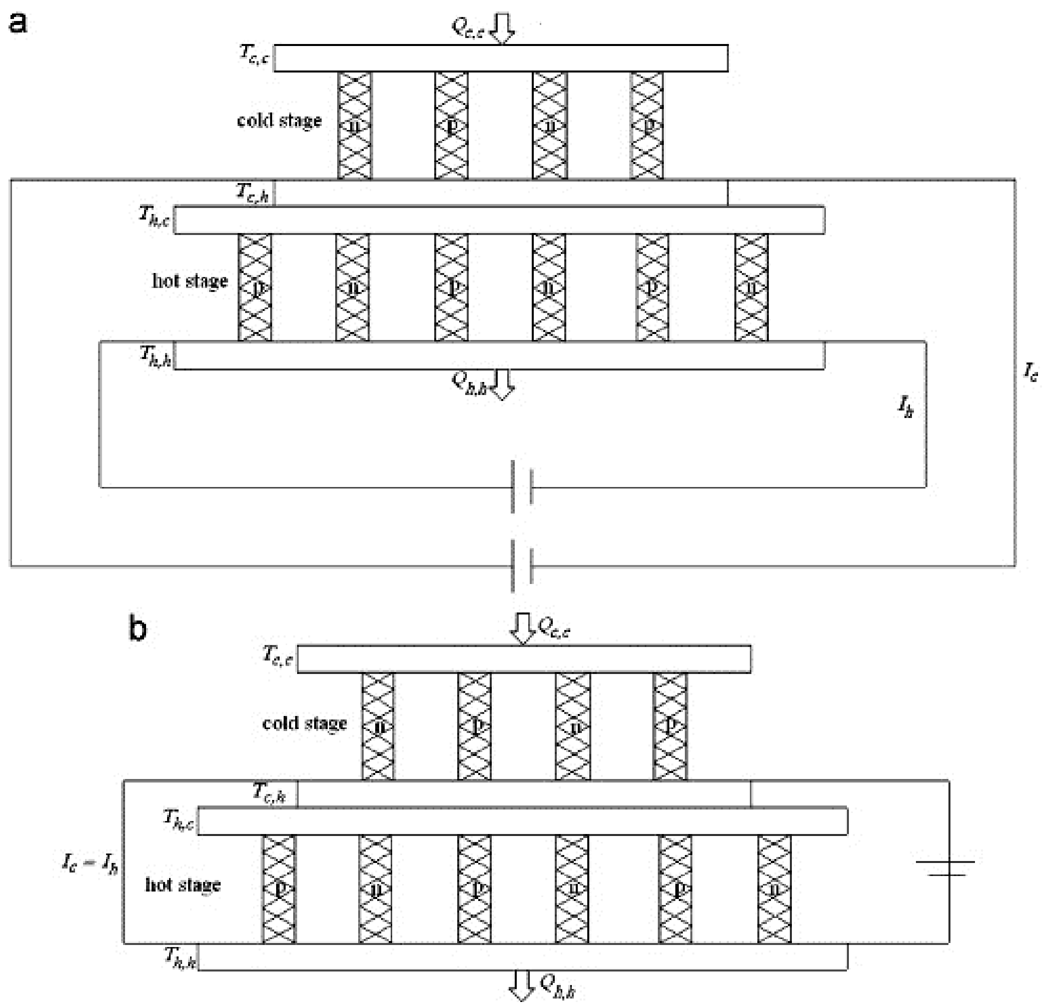

FIGURE 2. Two stage TEC (a) Electrically separated; (b) Electrically connected in series [14].

temperature. Therefore, when large temperature difference is required then two stage TECs should be used [13]. Basically, two-stage TECs are commercially arranged in cascade. The two-stage TECs are arranged in two different design configurations namely electrically separated and electrically connected in series. Fig. 2 presents the different configurations of two-stage TECs [14].

Chen *et al.* [15] analyzed the performance of a two-stage TE heat pump system driven by a two-stage TE generator. Many researchers [1], [16]–[20] had analysed the two stage TECs for optimization of COP or for best layout of the TE module. Cheng and Shih [14] described the thermal model of the two stage TECs. It is described as below.

The cascade two stage TECs are stacked one on the top of the other (Fig. 2). Here in this arrangement the top stage is the cold stage and the bottom stage is the hot stage. In Fig. 2, $Q_{c,c}$ and $Q_{h,h}$ are the cooling capacities of the cold side of the cold stage and the heat rejected at the hot side of hot stage respectively. $T_{c,c}$, $T_{c,h}$, $T_{h,c}$ and $T_{h,h}$ are the temperatures of the cold side of the cold stage, hot side of the cold stage, cold side of the hot stage and hot side of the hot stage respectively. I_c and I_h are the input currents to the cold stage and the hot stage respectively. n And p stand for n-type and p-type TE modules respectively. The COP of the two stage TECs is given as follows:

$$COP = \frac{Q_{c,c}}{Q_{hh} - Q_{cc}} \tag{4}$$

where, $Q_{c,c}$ and $Q_{h,h}$ are obtained by heat balance at relevant junction of TECs.

$$Q_{c,c} = \frac{N_t}{r+1}\left[\alpha_c I_c T_{c,c} - \frac{1}{2} I_c^2 R_c - K_c \left(T_{c,h} - T_{c,c}\right)\right] \tag{5}$$

$$Q_{h,h} = \frac{N_t r}{r+1}\left[\alpha_h I_h T_{h,h} + \frac{1}{2} I_h^2 R_h - K_h \left(T_{h,h} - T_{h,c}\right)\right] \tag{6}$$

where, N_t is the total number of TE modules of two stages and r is the ratio of the number of TE modules between the hot stage (N_h) to the cold stage (N_c). α, R and K are the Seebeck coefficient, electrical resistance and thermal conductance of the cold stage and the hot stage respectively. The total thermal resistance (RS_t) existing between the interface of TECs is

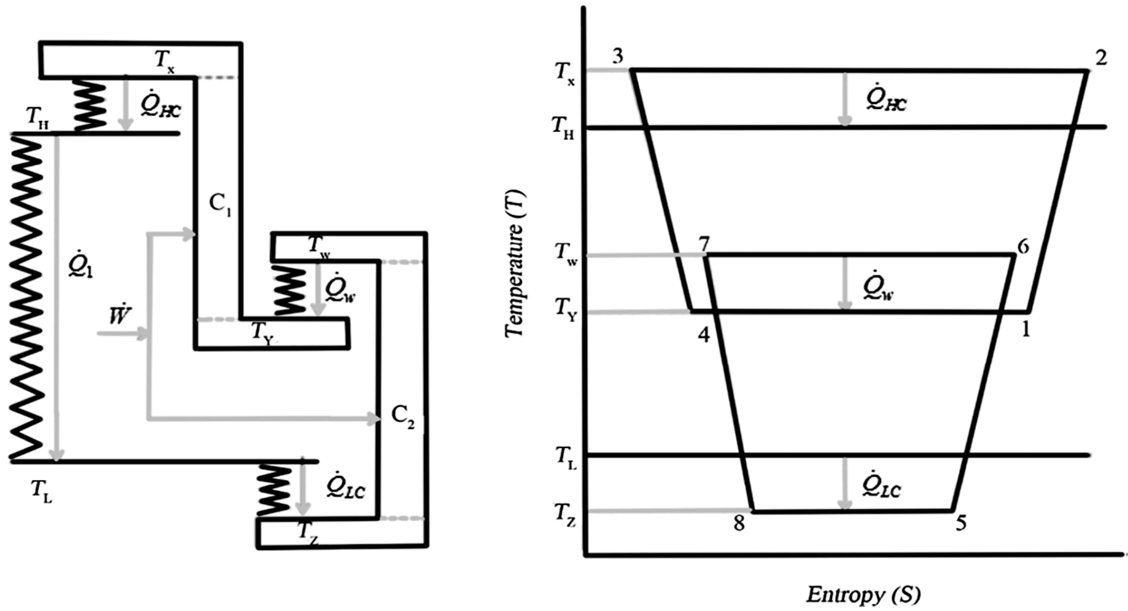

FIGURE 3. Two-stage combined irreversible heat pump model and its Temperature-Entropy diagram [22].

calculated as follows:

$$RS_t = RS_{sprd} + RS_{cont} \tag{7}$$

Here, RS_{sprd} and RS_{cont} are the spreading resistance and contact resistance between the interfaces of the two TECs respectively.

The heat rejected at the hot side of the cold stage ($Q_{c,h}$) and cooling capacity at the cold side of the hot stage ($Q_{h,c}$) are obtained by considering the heat balance at the interface of TECs and it is calculated as follows.

$$Q_{c,h} = \frac{N_t}{r+1}\left[\alpha_c I_c T_{c,h} + \frac{1}{2}I_c^2 R_c - K_c\left(T_{c,h} - T_{c.c}\right)\right] \tag{8}$$

$$Q_{h,c} = \frac{N_t}{r+1}\left[\alpha_h I_h T_{h,c} + \frac{1}{2}I_h^2 R_h - K_h\left(T_{h,h} - T_{h.c}\right)\right] \tag{9}$$

This case study is taken from the work of Hadidi (2017). The maximization of COP and cooling capacity is considered as objective functions which are calculated by (4) and (5) respectively.

The objective functions are governed by the three design variables whose ranges are given below:

$$4 \le I_c \le 11 \tag{10}$$

$$4 \le I_h \le 11 \tag{11}$$

$$2 \le r \le 7.33 \tag{12}$$

B. TWO STAGE IRREVERSIBLE HEAT PUMP

Heat pumps are widely used for transporting heat from low temperature sources to higher ones and are usually single-stage heat pumps [21]. However, there are some limitations in conventional single-stage compression heat pumps, for example, the inefficient performance, high discharge temperature and low performance of compressor especially in winter which make them less popular. With the purpose of gaining a higher range of temperature difference between the environment and heated space, two stage heat pump plants are developed and are widely used in industrial scale. Many authors had investigated the performance of single stage vapor compression and absorption heat pumps and refrigeration cycles employing finite time thermodynamics [22]. Fig. 3 illustrates the T–S diagram of the model [22].

This is a two stage irreversible heat-pump system. Because of a number of causes such as heat resistance, friction, internal losses and heat leak, the cycle differs from the ideal system. In the present study, the heat leak and friction losses are considered as internal losses and finite-rate heat transfer. The two cycles with two distinct working fluids might work within various temperature ranges. The heat exchanger between them transfers the heat from one to another to recover the heat between two cycles. There are a number of investigations in literature related to irreversible Carnot heat pump cycle with irreversibility of heat resistance, heat leak and internal loss [22]

This case study is considered from the work of Sahraie *et al.* [22]. In this study, the authors had developed mathematical models to optimize the performance of the two-stage irreversible heat pump (HP) while satisfying the imposed conditions. The objectives of this HP are as follows:

a. Maximization of co-efficient of performance (COP) and it is defined as:

$$COP = \frac{\dot{Q}_H}{W} = \frac{1-R}{1-\frac{T_Y T_Z}{I_1 I_2 T_X T_W}} \tag{13}$$

Here, R denotes the heat leakage percentage and is assumed to be an identified constant. T_W, T_X, T_Y and T_Z are known as the temperatures of warm working fluid of the second cycle, warm working fluid of the first cycle, cold working fluid of the first cycle and cold working fluid of the second cycle respectively. I_1 and I_2 are known as irreversibility of first stage and second stage respectively.

b. Maximization of heat transfer rate (q_H) and is defined as:

$$q_H = \frac{\dot{Q}_H}{A} = (1-R) \times \left[\frac{1}{U_H (T_X - T_H)} + \frac{T_Y T_Z}{I_1 I_2 T_X T_W U_L (T_L - T_Z)} + \frac{TY}{I_1 T_X U_W (T_W - T_Y)} \right]^{-1} \tag{14}$$

[c.] Maximization of thermo-economic benchmark of absorption heat pump (F):

$$F = (1-R) \times \left[\left(\frac{1}{U_L (T_L - T_Z)} - 1 \right) \frac{T_Y T_Z}{I_1 I_2 T_X T_W} + \frac{k}{U_H (T_X - T_H)} + \frac{k T_Y}{I_1 T_X U_W (T_W - T_Y)} + 1 \right]^{-1} \tag{15}$$

Design variables and there ranges are as follows:

$$412.4 \leq T_X \leq 448.8$$
$$249.6 \leq T_Z \leq 265.6$$
$$0.9041 \leq u \leq 0.9715$$
$$0.1 \leq k \leq 1$$

where, $u = T_Y/T_W$ & $k = a/b$ and $I_1 = I_2 = 1.05$, $R = 0.02$, $U_H = U_L = U_W = 0.5$, $T_H = 400K$, $T_L = 273K$.

C. PLATE-FIN HEAT EXCHANGER

In recent years the application of advanced optimization algorithms for design problems of PFHE has gained much momentum. Mixed-Integer-Non-Linear-Programming was used for the design optimization of PFHE system with discrete and continuous variables [23]; Traditional methods were also used for carrying out the optimization of these systems having a complex mathematical model [24]. Simulated annealing (SA) [25], artificial neural networks [26] and evolutionary algorithms [27]–[32] had been used for the thermal design optimization of heat exchanger.

The details of mathematical model considered from the work of Hadidi [31] are as follows: Effectiveness of an unmixed cross-flow heat exchanger is expressed as [31]:

$$\varepsilon = 1 - \exp\left[\left(\frac{1}{C} \right) NTU^{0.22} \left\{ \exp\left(-C \cdot NTU^{0.78} \right) - 1 \right\} \right] \tag{16}$$

Here, C is known as heat capacity ratio and defined as:

$$C = \frac{C_{\min}}{C_{\max}} = \frac{\min(C_h, C_c)}{\max(C_h, C_c)} \tag{17}$$

Here, suffix h and c denotes the hot and cold side respectively. Fig. 4 presents the layout of a PFHE.

Outlet temperatures of hot fluid ($T_{h,o}$) and cold fluid ($T_{c,o}$) are calculated as:

$$T_{h,o} = T_{h,i} - \varepsilon C_{\min}/C_h (T_{h,i} - T_{c,i}) \tag{18}$$
$$T_{c,o} = T_{c,i} + \varepsilon C_{\min}/C_c (T_{h,i} - T_{c,i}) \tag{19}$$

Now, the number of transfer units (NTU) can be calculated as:

$$\frac{1}{NTU} = \frac{C_{\min}}{UA_t} \tag{20}$$

A_t is the total heat transfer area of plate-fin heat exchanger and U is known as overall heat transfer co-efficient. It is defined as:

$$\frac{1}{UA} = \frac{1}{(hA)_h} + \frac{1}{(hA)_c} \tag{21}$$

Convective-heat transfer coefficient is calculated as:

$$h = j.G.C_p.P_r^{-2/3} \tag{22}$$

Here, j is known as Colburn factor [31]; G is mass flux and defined as:

$$j = 0.6522(\mathrm{Re})^{-0.5403}(\alpha)^{-0.1541}(\delta)^{0.1499}(\gamma)^{-0.0678} \times \left[1 + 5.269 \times 10^{-5} (\mathrm{Re})^{1.34} (\alpha)^{0.504} (\delta)^{0.456} (\gamma)^{-1.055} \right]^{0.1} \tag{23}$$

$$G = m/A_f \tag{24}$$

Here, α, δ and γ are the geometrical parameters of PFHE. Re is known as Reynolds number and defined as:

$$R_e = \frac{G \cdot D_h}{\mu} \tag{25}$$

Here μ is dynamic viscosity and D_h is known as hydraulic diameter and can be evaluated as:

$$D_h = \frac{4(c - t_f)(b - t_f)x}{2\left((c - t_f)x + (b - t_f)x + t_f (b - t_f) \right) + t_f (c - t_f) - t_f^2} \tag{26}$$

Here, t_f, b, c and x are the thickness, height, pitch and length of the fin, respectively. A_f is known as free flow area and is evaluated as:

$$A_{f,h} = L_h N_p (b_h - t_{f,h}(1 - n_h \cdot t_{f,h}) \tag{27}$$
$$A_{f,c} = L_c \cdot (N_p + 1)((b_h - t_{f,h})(1 - n_h \cdot t_{f,h}) \tag{28}$$

L_c and L_h are the hot and cold flow length. Heat transfer area of hot side and cold side is calculated as:

$$A_h = L_h L_c N_p [1 + 2n_h (b_h - t_{f,h})] \tag{29}$$
$$A_c = L_h L_c (N_p + 1)[1 + 2n_c (b_c - t_{f,c})] \tag{30}$$

Now, the total heat transfer area is calculated as:

$$A_t = A_h + A_c \tag{31}$$

And the rate of heat transfer is evaluated as:

$$Q = \varepsilon C_{min} (T_{h,i} - T_{c,i}) \tag{32}$$

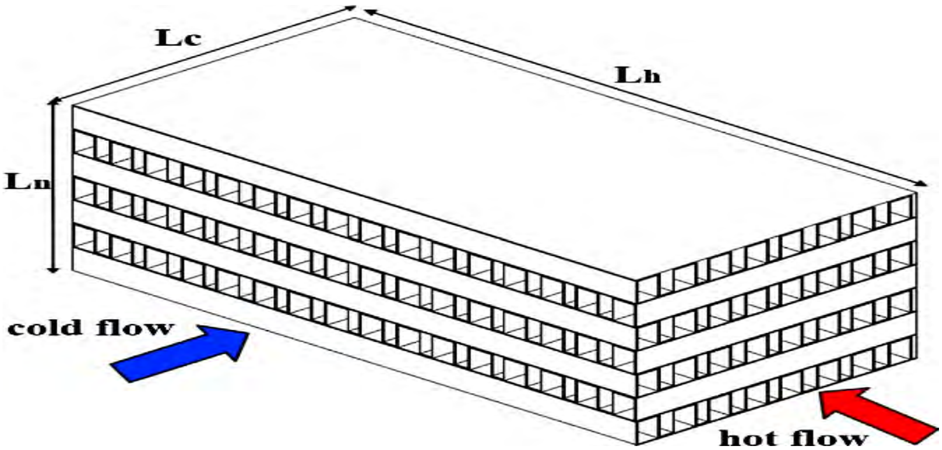

FIGURE 4. Detailed layout of plate-fin heat exchanger [29].

Due to friction, pressure drop is caused. Hot and cold side pressure drop is evaluated as:

$$\Delta P_h = \frac{2f_h L_h G_h^2}{\rho_h D_{h.h}} \tag{33}$$

$$\Delta P_c = \frac{2f_c L_c G_c^2}{\rho_c D_{h,c}} \tag{34}$$

Here, for an off-strip fin fanning factor f is evaluated as:

$$f = 9.6243(\mathrm{Re})^{-0.7422}(\alpha)^{-0.1856}(\delta)^{0.3053}(\gamma)^{-0.2659} \times \left[1+7.669\times 10^{-8}(\mathrm{Re})^{4.429}(\alpha)^{0.920}(\delta)^{3.767}(\gamma)^{0.236}\right]^{0.1} \tag{35}$$

The allowed ranges of the design variables are shown below [31]:

- Stream flow length of hot side, $L_h(\mathrm{m}) = 0.1 \leq L_h \leq 1$.
- Stream flow length of cold side, $L_c(\mathrm{m}) = 0.1 \leq L_c \leq 1$.
- Fin height, b (mm) $= 2 \leq b \leq 10$.
- Fin thickness, $t_f(\mathrm{mm}) = 0.1 \leq t_f \leq 0.2$.
- Frequency of fin $(n) = 100 \leq n \leq 1000$.
- Offset length, $x(\mathrm{mm}) = 1 \leq x \leq 10$.
- Fin layers number $(N_P) = 1 \leq N_p \leq 200$.

Out of these parameters, N_P is a discrete variable and rest of the variables are continuous in nature.

Nine constraints are imposed on the PFHE design, in order to get the specific duty of heat exchanger with limitations on mathematical model and geometries, are defined as follows:

The value of Re for hot and cold steam flow must be in the following range:

Constraint 1: $120 \leq Re_c \leq 10^4$

Constraint 2: $120 \leq Re_h \leq 10^4$

The equations used for the calculation of Colburn factor and fanning factor are to be used only when the values Re of the suggested design falls in the above given range. The geometrical parameters of the PFHE must be in the following ranges:

Constraint 3: $0.134 \leq \alpha \leq 0.997$

Constraint 4: $0.041 \leq \gamma \leq 0.121$

Constraint 5: $0.012 \leq \delta \leq 0.048$

Eqs. of Colburn factor and fanning factor) are valid only for above ranges.

No-flow length (L_n) of PFHE is also restricted:

Constraint 6: $L_n = 1.5$

The value of $\mathrm{L_n}$ is evaluated with the help of following equation:

Constraint 7:

$$L_n = b - 2t_p + N_p(2b + 2t_p) \tag{36}$$

Heat duty required for the PFHE is also taken as constraint in order to meet the minimum heat duty [28]:

Constraint 8: $Q \geq 1069.8$ kW

Allowed pressure drop of hot side and cold side:

Constraint 9: $\Delta P_h \leq 9.5$ kPa and $\Delta P_c \leq 8$ kPa

Four different objectives are taken up for the design optimization of PFHE. The details of the objective functions considered from the work of Hadidi [31] described below.

First objective is the minimization of total annual cost which is the sum of initial investment cost C_{in} and operational cost C_{op}. Detailed mathematical model for the calculation of these costs is described as follows:

$$C_{in} = a \cdot C_a \cdot A_t^{n1} \tag{37}$$

$$C_{op} = \left[k_{el}\tau \frac{\Delta P_h}{\eta}\frac{m_h}{\rho_h}\right] + \left[k_{el}\tau \frac{\Delta P_c}{\eta}\frac{m_c}{\rho_c}\right] \tag{38}$$

and

$$C_{tot} = C_{in} + C_{op} \tag{39}$$

In the above equations, $\mathrm{C_a}$ is cost per unit of A_t; n1 is exponent value; k_{el} is electricity price; τ is hours of operation and η is known as compressor efficiency. In (37), a is known as annual cost coefficient and described as follows:

$$a = \frac{i}{1-(1+i)^{-ny}} \tag{40}$$

where, i is rate of interest and ny is time of depreciation.

Minimization of heat transfer area required for proper heat transfer is the second objective of this study. Total area required is calculated from the (31). This design equation is linked with investment cost of the considered PFHE. Third objective is also to be minimized which is a combined function of pressure drops of cold side and hot side fluids. The objective of this case is linked with the operating cost of the PFHE system. A combined normalized function of pressure drops is used in the optimization study and it is defined by the following equation:

$$O(x) = \frac{\Delta P_h}{P_{h,\max}} + \frac{\Delta P_c}{P_{c,\max}} \tag{41}$$

Maximization of effectiveness is considered as the fourth objective. Calculation of the effectiveness of the heat exchanger is based upon (16).

D. TRANSCRITICAL CYCLES

Due to increasing greenhouse effect of hazardous refrigerants on the environment, it has become need of the world to use eco-friendly refrigerants for heating or cooling applications. Carbon Dioxide (CO_2) can be used as a substitute to the other harmful refrigerants. The advantages of selecting CO_2 (R744) as working fluid are: low cost, non-toxicity and non-flammability. The main advantages of using CO_2 as refrigerant in comparison to other refrigerants are: having zero Ozone layer depletion layer index and low global warming potential. The environmental damages can be minimized by taking the advantages of transcritical (TC) cycles. A TC cycle is a type of thermodynamic cycle in which the working fluid goes under both critical and subcritical state [37].

Sarkar *et al.* [33] performed the optimization of TC CO_2 heat pump cycle for simultaneous applications of heating and cooling. The objective functions considered in their study were maximization of coefficient of performance, minimization of discharge pressure and maximization of output temperature. A theoretical optimization method was used by Rezayan and Behbahaninia [34] for minimizing the annual costs of a cascade system with ammonia and CO_2 as refrigerants.

Fazelpour and Morosuk [35] had developed a cost and energy efficient TC refrigeration system. It was recommended that by using the economizer as an supplementary component for single-stage TC refrigeration system can reduce the total cost about 14%. Bai *et al.* [36] carried out an advanced analysis of an ejector expansion transcritical TC refrigeration system. The study had suggested that compressor with highest avoidable endogenous exergy destruction required to improve performance of refrigerator.

Khanmohamadi *et al.* [37] did the modeling and thermal and economic optimization of a modified TC CO_2 refrigeration cycle by using multiobjective genetic algorithm (GA). The maximization of cooling capacity and minimization of cost were considered as objectives. The authors had used decision making techniques in order to get the best set of solution among the nondominated solutions. Ahmadi *et al.* [38] did the exergy and thermodynamic analysis, and multiobjective (MO) optimization of a TC CO_2 power cycle by using nondominated sorting GA (NSGA-II). This cycle was powered by geothermal energy having heat sink in the form of liquefied natural gas. The minimization of total heat exchange area and maximization of exergetic performance criteria, and exergy efficiency were considered as objective functions. The authors had used three decision making techniques in order to get the best set of solution among the nondominated solutions.

Ahmadi *et al.* [39] performed thermodynamic analysis and MO optimization of a TC CO_2 power cycle by using NSGA-II. This cycle was powered by solar energy having heat sink in the form of liquefied natural gas. The maximization of thermal efficiency and solar fraction and minimization of total cost of the system were considered as the objective functions. The authors had used three decision making techniques in order to get the best set of solution among the nondominated solutions.

1) MODIFIED TRANSCRITICAL CO_2 REFRIGERATION CYCLE

A graphical representation of the modified TC CO_2 refrigeration cycle with its parts is shown in Fig.5 [37]. It is having nine important parts which are included in the modified TC CO_2 refrigeration cycle. These are namely, ejector, evaporator, low-pressure compressor, internal heat exchanger, high-pressure compressor, expansion valve, separator, gas cooler and intercooler.

Khanmohammadi *et al.* [37] developed a mathematical model to optimize the modified transcritical CO_2 refrigeration cycle. The design variables considered in their study were, cooling water temperature (T_{gc}), gas cooler pressure (P_{gc}), evaporator temperature (T_e) and extracted mass flow rate (α). The objective functions consisted in this work was the maximization of cooling capacity (Q) and minimization of cost rate (Z). The equations of the objectives, (42) and (43), are defined as shown at the bottom of the next page.

Where,

$$\begin{aligned}
C_{23} &= a_{01} + a_{11}{*}P_{gc} + a_{21}{*}T_{gc} + a_{31}{*}(P_{gc}^2) + a_{41*}T_{gc}^2 \\
&\quad + a_{51}{*}P_{gc}{*}T_{gc}; \\
C_{13} &= a_{02} + a_{12}{*}\alpha + a_{22}{*}T_{gc} + a_{32}{*}\alpha^2 + a_{42}{*}T_{gc}^2 \\
&\quad + a_{52}{*}\alpha{*}T_{gc}; \\
C_{34} &= a_{03} + a_{13}{*}T_{gc} + a_{23}{*}T_e + a_{33}{*}T_{gc}^2 + a_{43}{*}T_e^2 \\
&\quad + a_{53}{*}T_e{*}T_{gc}; \\
C_{2313} &= a_{04} + a_{14}{*}C_{23} + a_{24}{*}C_{13} + a_{34}{*}C_{23}^2 + a_{44}{*}C_{13}^2 \\
&\quad + a_{54}{*}C_{23}{*}C_{13};
\end{aligned}$$

Where,

$$\begin{aligned}
Z_{14} &= c_{01} + c_{11}{*}\alpha + c_{21}{*}T_e + c_{31}{*}\alpha^2 + c_{41}{*}T_e^2 \\
&\quad + c_{51}{*}\alpha{*}Te; \\
Z_{34} &= c_{02} + c_{12}{*}T_{gc} + c_{22}{*}T_e + c_{32}{*}T_{gc}^2 + c_{42}{*}T_e^2 \\
&\quad + c_{52}{*}T_{gc}{*}T_e; \\
Z_{2214} &= c_{03} + c_{13}{*}P_{gc} + c_{23}{*}Z_{14} + c_{33}{*}P_{gc}^2 + c_{43}{*}Z_{14}^2 \\
&\quad + c_{53}{*}P_{gc}{*}Z_{14}; \\
Z_{3422} &= c_{04} + c_{14}{*}Z_{34} + c_{24}{*}P_{gc} + c_{34}{*}Z_{34} + c_{44}{*}P_{gc}^2 \\
&\quad + c_{54}{*}P_{gc}{*}Z_{34};
\end{aligned}$$

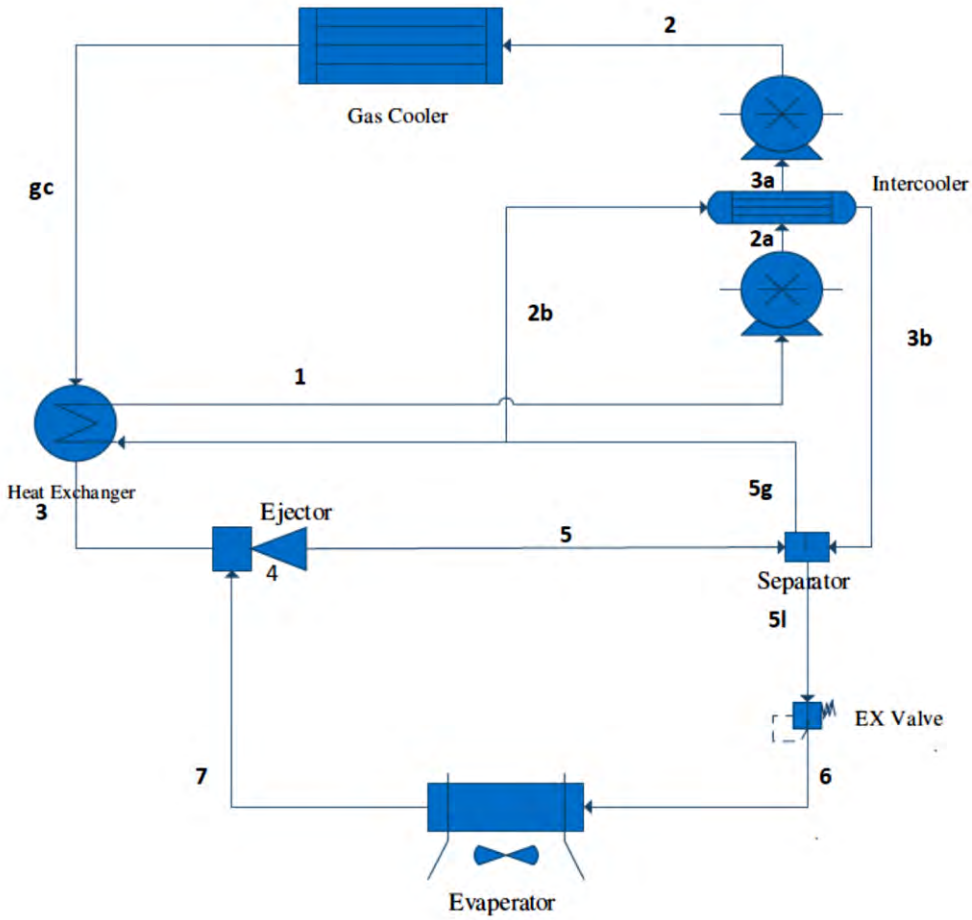

FIGURE 5. Schematic diagram of modified two-stage refrigeration cycle [37].

The values of constant used in Eqs. (42) and (43) can be obtained from [37].

The ranges of design variables are as follows:

- $35°C \leq T_{gc} \leq 55°C$, Gas cooler temperature;
- $75 \text{ bar} \leq P_{gc} \leq 140 \text{ bar}$, Gas cooler pressure;
- $-30°C \leq T_e \leq -1°C$, evaporator temperature;
- $0.1 \leq \alpha \leq 0.9$, extracted mass flow rate.

2) TRANSCRITICAL CO_2 HEAT PUMP CYCLE FOR SIMULTANEOUS HEATING AND COOLING APPLICATIONS

The CO_2 vapor compression refrigeration system was developed in 1850, subsequently it was used for many years. It was mainly used in marine. Many problems were found with the early CO_2 based systems because of having low critical temperature of CO_2. With the development of halocarbon refrigerants, CO_2 was slowly rolled down from the applications of air conditioning and refrigeration. However, halocarbon refrigerants deplete the Ozone layer and hence negative effect on environment. This renewed a new interest in natural refrigerants such as CO_2 [33]. A schematic diagram of CO_2 based heat pump of heating and cooling system having its main component are shown in Fig. 6 [33].

Sarkar *et al.* [33] presented the optimization of a TC CO_2 heat pump. It is used for cooling and heating applications together. A Mathematical model was developed for maximization of COP, minimization of discharge pressure (P_{opt}) and maximization of output temperature (t_2) in terms of evaporation temperature (t_{ev}) and cooler exit temperature (t_3). The details of the objective functions are as follows:

$$COP_{\max} = 48.2 + 0.2t_{ev} + 0.05t_3 (t_3 - 48.5) - 0.0004 \cdot t_3^3 \tag{44}$$

$$P_{opt} = 4.9 + 2.256 \cdot t_3 - 0.17t_{ev} + 0.002 \cdot t_3^2 \tag{45}$$

$$Q_{\max} = a_{05} + a_{15} \cdot C_{2313} + a_{25} \cdot C_{34} + a_{35} \cdot C_{2313}^2 + a_{45} \cdot C_{34}^2 + a_{55} \cdot C_{2313} \cdot C_{34} \tag{42}$$

$$Z_{\min} = c_{05} + c_{15} \cdot Z_{2214} + c_{25} \cdot Z_{3422} + c_{35} \cdot Z_{2214}^2 + c_{45} \cdot Z_{3422}^2 + c_{55} \cdot Z_{2214} \cdot Z_{3422} \tag{43}$$

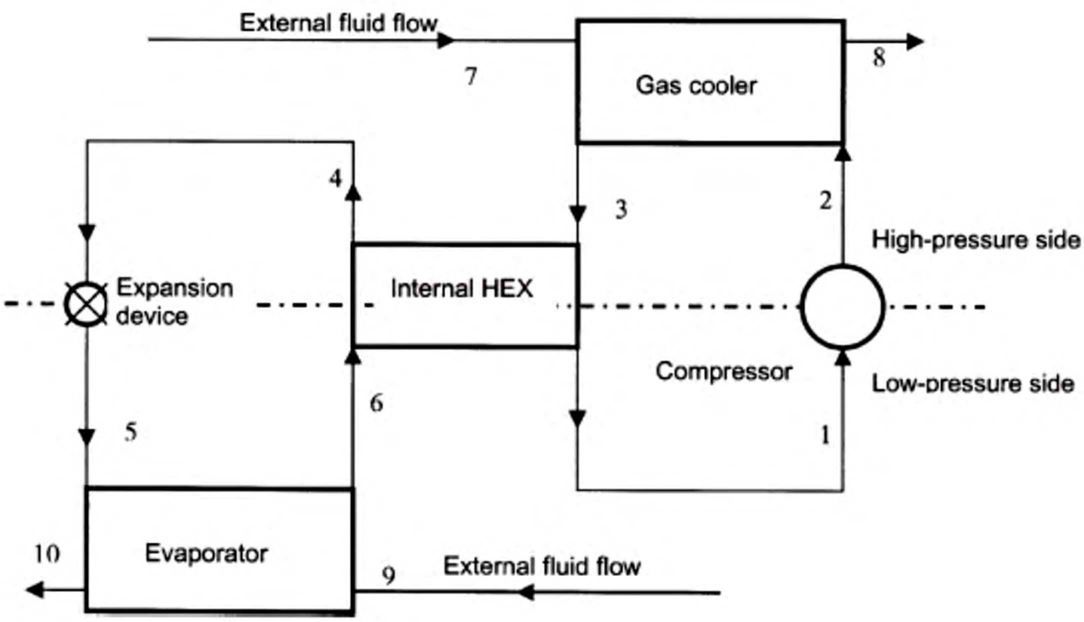

FIGURE 6. Line diagram of a TC CO_2 system [33].

$$t_2 = -10.65 + 3.78 \cdot t_3 - 1.44 \cdot t_{ev} - 0.0188 \cdot t_3^2 + 0.009 \cdot t_{ev}^2 \tag{46}$$

E. IRREVERSIBLE CARNOT POWER CYCLE

Analysis of the irreversible thermodynamic systems has gained importance especially after the petrol crisis happened in 1970s [40]. This engine provides us more realistic results than reversible Carnot cycle. Maximum available work from an irreversible system was analysed by Wu [41]. Ecological function criterion (ECF) was proposed by Angulo-Brown [42] which is used for the analysis of irreversible Carnot power cycle. Yan [43] suggested to use T_0 (heat sink temperature) on the place of T_L (cold reservoir temperature).

Many research works are found in the literature regarding ecological optimization of irreversible Carnot power cycle [44]. Another thermo-ecological criterion called ecological coefficient of performance (ECOP) was presented and applied to various thermodynamic cycles by Ust *et al.* [45]. Similarly, to determine the relationship between exergy and exergy destruction for a cycle, performance coefficient so called exergetic performance criteria (EPC) was presented by Ust *et al.* [46]. To obtain a method for the application of exergy concept in finite time thermodynamic (FTT), a number of studies were published by several authors [47]. A new criterion for assessing actual thermal cycles was submitted by Acıkkalp [48]. Ahmadi *et al.* [49] had used multiobjective genetic algorithm (MO-GA) to optimize the thermal performance of irreversible Carnot power cycle. The results of MO-GA were further analyzed by using TOPSIS, LINMAP and fuzzy logic.

The first law efficiency (η), the exergetic performance criteria (EPC) and the maximum available work (MAW) are the three objective functions considered for the optimization and given as follows.

$$\eta = 1 - Ix \tag{47}$$

Ecological function criteria:

$$ECF = \frac{(T_L - xT_H)\,(T_H\,(IT_o x + T_L\,(Ix - 1)) - T_L T_o)\,yz}{T_L T_H x\,(y + 1)\,(1 + y)} \tag{48}$$

Maximum available work:

$$MAW = \frac{(T_L - IxT_o)\,(xT_H - T_L)\,yz}{T_L x\,(y + I)\,(1 + y)} \tag{49}$$

Here, I is the irreversibility parameter. T_H and T_h are the heat source temperature and hot working fluid temperature (K), respectively, and k_H is the heat conductance (kW/K) between the hot temperature heat source and working fluid. T_L and T_c are the heat sink temperature and cool working fluid temperature (K), respectively, and k_L is the heat conductance (kW/K) between the low temperature heat sink and working fluid.

Three decision variables have been chosen for our study, which are as follows:

x: ratio of fluid temperature $\left(x = \frac{T_c}{T_h}\right)$

y: parameter of the heat conductance rate $\left(y = \frac{K_L}{K_H}\right)$

z: the sum of heat conductance rate $(z = K_L + K_H)$

$$0.5 \le y \le 1$$
$$1.08 \le z \le 1.8$$
$$0.45 \le x \le 0.7$$

TABLE 1. Optimization results of individual objectives for electrically separated TEC.

	GA [14]		PSO [19]		ABC [19]		TLBO [19]		Modified-TLBO [19]		CRO [20]		MO-SAMP Jaya	
	Max $Q_{c,c}$	Max COP	Max $Q_{c,c}$	Max COP	Max $Q_{c,c}$	Max COP	Max $Q_{c,c}$	Max COP	Max $Q_{c,c}$	Max COP	Max $Q_{c,c}$	Max COP	Max $Q_{c,c}$	Max COP
RS_j = 0.02 cm² K/W														
I_h (A)	8.613	6.611	9.2671	7.0044	9.3978	6.7299	9.3077	6.7299	9.3077	6.7299	7.596	7.376	9.13323	6.80538
I_c(A)	7.529	7.592	7.8411	7.3077	7.6967	7.581	7.7146	7.581	7.7146	7.581	9.290	6.949	7.44642	7.23250
r	5.25	6.143	5.25	5.25	5.25	6.143	5.25	6.143	5.25	6.143	5.37	6.023	5.29626	5.87360
N_c	8	7	8	8	8	7	8	7	8	7	8	7	8	7
$Q_{c,c}$ (W)	0.755	–	0.7833	0.6141	0.7837	0.5968	0.784	0.5968	0.784	0.5968	0.758	0.6006	**0.78880**	0.61851
COP	–	0.019	0.015	0.0191	0.015	0.0192	0.015	0.0192	.015	0.0192	-	0.0185	0.01532	**0.01938**
	Max $Q_{c,c}$	Max COP	Max $Q_{c,c}$	Max COP	Max $Q_{c,c}$	Max COP	Max $Q_{c,c}$	Max COP	Max $Q_{c,c}$	Max COP	Max $Q_{c,c}$	Max COP	Max $Q_{c,c}$	Max COP
RS_j = 0.2 cm² K/W														
I_h (A)	8.652	6.769	9.3278	6.5338	9.3278	6.5338	9.3278	6.5338	9.3278	6.5338	7.825	7.588	9.35051	6.71639
I_c(A)	7.805	7.465	8.0121	7.8165	8.0121	7.8165	8.0121	7.8165	8.0121	7.8165	9.311	6.790	7.51670	7.28610
r	5.25	6.143	5.25	6.143	5.25	6.143	5.25	6.143	5.25	6.143	5.34	6.011	5.02678	5.71820
N_c	8	7	8	7	8	7	8	7	8	7	8	7	8	8
$Q_{c,c}$ (W)	0.838	–	0.8826	0.6544	0.8826	0.6544	0.8826	0.6544	0.8826	0.6544	0.8409	0.6553	**0.89600**	0.68259
COP	–	0.021	0.0168	0.0219	0.0168	0.0219	0.0168	0.0219	0.0168	0.0219	-	0.0208	0.01715	**0.02228**
	Max $Q_{c,c}$	Max COP	Max $Q_{c,c}$	Max COP	Max $Q_{c,c}$	Max COP	Max $Q_{c,c}$	Max COP	Max $Q_{c,c}$	Max COP	Max $Q_{c,c}$	Max COP	Max $Q_{c,c}$	Max COP
RS_j = 2 cm² K/W														
I_h (A)	9.29	5.204	9.413	4.8169	9.609	4.5779	9.609	4.4163	9.609	4.4163	11	10.690	9.625534	4.549142
I_c(A)	9.41	9.889	10.8829	10.2275	11	10.4732	11	10.722	11	10.722	9.592	4.576	11.0000	10.911666
r	4.556	5.25	4.556	6.143	4.556	7.333	4.556	7.333	4.556	7.333	4.703	7.33	4.614992	7.330000
N_c	9	8	9	7	9	6	9	6	9	6	9	6	9	6
$Q_{c,c}$ (W)	2.103	–	2.25	1.3329	2.254	1.2381	2.254	1.201	2.254	1.201	2.187	1.209	**2.284225**	1.249334
COP	–	0.061	0.0406	0.0647	0.0393	0.0652	0.0393	0.0654	0.0393	0.0654	-	0.063	0.039678	**0.065771**

For choosing the best Pareto optimal solution, a quantity measure index known as deviation index is evaluated. The deviation index defines the deviation of each solution from the ideal and non-ideal solutions and can be calculated using (50) and (51), shown at the bottom of this page [10].

The next section presents the application of the MO-SAMP Jaya algorithm for the design optimization of selected thermal devices namely TEC, irreversible HP, PFHE and two basic thermal cycles namely transcritical cycle, and irreversible Carnot power cycle.

IV. RESULTS AND DISCUSSION

A. THERMO-ELECTRIC COOLER

The results obtained by using MO-SAMP Jaya algorithm are presented below. Two different case studies namely electrically separated and eclectically connected are considered. Table 1 presents the results obtained by MO-SAMP Jaya algorithm and their comparison for the thermal performance optimization of two-stage electrically separated TEC. Table shows the comparison of results for single objective optimization. It can be observed from this table that the results obtained by using MO-SAMP Jaya algorithm are better as compared to the results of GA [14], PSO, ABC, TLBO, modified-TLBO [19] and CRO algorithms [20] for each value of RS_t. When the value of $RS_t = 0.02$ cm^2 K/W is considered. The value of COP obtained by MO-SAMP Jaya algorithm is increased by 1.808%, 1.29%, 0.775%, 0.775%, 0.775% and 4.392% as compared to the results of GA, PSO, ABC, TLBO, MOTLBO and CRO algorithms. Subsequently, the value cooling capacity is increased by 4.28%, 0.697%, 0.646%, 0.608%, 0.608% and 3.90% as compared to the results of GA [14], PSO, ABC, TLBO, modified-TLBO [19] and CRO [20] algorithms.

When the value of $RS_t = 0.2$ cm^2 K/W is considered, the value of COP obtained by MO-SAMP Jaya algorithm is increased by 5.74%, 1.705%, 1.705%, 1.705%, 1.705% and 6.64% as compared to the results of [14], PSO, ABC, TLBO, modified-TLBO [19] and CRO [20] algorithms.. Subsequently, the value cooling capacity is increased by 6.6473%, 1.495%, 1.495%, 1.495%, 1.495% and 6.14% as compared to the results of GA [14], PSO, ABC, TLBO, modified-TLBO [19] and CRO [20] algorithms.. When the value of $RS_t = 0.02$ cm^2 K/W is considered. The value of COP obtained by MO-SAMP Jaya algorithm is increased by 7.253%, 1.612%, 0.868%, 0.564%, 0.54% and 4.213% as compared to the results of GA [14], PSO, ABC, TLBO, modified-TLBO [19] and CRO [20] algorithms. Subsequently, the value cooling capacity is increased by 7.93%,

$$d_+ = \sqrt{\left(EPC_n - EPC_{n,ideal}\right)^2 + \left(\eta_n - \eta_{n,ideal}\right)^2 + \left(MAW_n - MAW_{n,ideal}\right)^2} \quad (50)$$

$$d_- = \sqrt{\left(EPC_n - EPC_{n,nnon-ideal}\right)^2 + \left(\eta_n - \eta_{n,non-ideal}\right)^2 + \left(MAW_n - MAW_{n,non-ideal}\right)^2}$$

$$d = \frac{d_+}{(d_+) + (d_-)} \quad (51)$$

TABLE 2. Optimization results of individual objectives for electrically connected TEC.

	GA [14]		PSO [19]		ABC [19]		TLBO [19]		Modified-TLBO [19]		MO-SAMP Jaya	
	Max $Q_{c,c}$	Max COP	Max $Q_{c,c}$	Max COP	Max $Q_{c,c}$	Max COP	Max $Q_{c,c}$	Max COP	Max $Q_{c,c}$	Max COP	Max $Q_{c,c}$	Max COP
RS_j = 0.02 cm^2 K/W												
I_h (A)	8.415	7.27	8.5737	7.1558	8.5737	7.1558	8.5737	7.1558	8.5737	7.1558	8.36134	6.99632
I_c(A)	8.415	7.27	8.5737	7.1558	8.5737	7.1558	8.5737	7.1558	8.5737	7.1558	8.36134	6.99632
r	6.143	5.25	6.143	5.25	6.143	5.25	6.143	5.25	6.143	5.25	6.09197	5.56300
N_c	7	8	7	8	7	8	7	8	7	8	7	8
$Q_{c,c}$ (W)	0.73	–	0.7479	0.6405	0.7479	0.6405	0.7479	0.6405	0.7479	0.6405	**0.75117**	0.64292
COP	–	0.019	0.0159	0.0191	0.0159	0.0191	0.0159	0.0191	0.0159	0.0191	0.01666	**0.01968**
	Max $Q_{c,c}$	Max COP	Max $Q_{c,c}$	Max COP	Max $Q_{c,c}$	Max COP	Max $Q_{c,c}$	Max COP	Max $Q_{c,c}$	Max COP	Max $Q_{c,c}$	Max COP
RS_j = 0.2 cm^2 K/W												
I_h (A)	8.663	7.135	8.5978	7.4962	8.7375	7.4962	8.7375	7.1681	8.7375	7.1681	8.475959	6.992917
I_c(A)	8.663	7.135	8.5978	7.4962	8.7375	7.4962	8.7375	7.1681	0.7375	7.1681	8.475959	6.992917
r	6.143	5.25	6.143	5.25	6.143	5.25	6.143	6.143	6.143	6.143	5.837901	5.316666
N_c	7	8	7	8	7	8	7	8	7	8	7	8
$Q_{c,c}$ (W)	0.818	–	0.8328	0.7157	0.8338	0.7157	0.8338	0.7098	0.8338	0.7098	**0.846712**	0.716019
COP	–	0.02	0.0177	0.0213	0.0172	0.0213	0.0172	0.0215	0.0172	0.0215	0.018511	**0.022157**
	Max $Q_{c,c}$	Max COP	Max $Q_{c,c}$	Max COP	Max $Q_{c,c}$	Max COP	Max $Q_{c,c}$	Max COP	Max $Q_{c,c}$	Max COP	Max $Q_{c,c}$	Max COP
RS_j = 2 cm^2 K/W												
I_h (A)	9.482	7.133	9.7236	7.305	10.1207	7.305	10.387	7.305	10.387	7.305	10.162302	7.239582
I_c(A)	9.482	7.133	10.4581	7.305	10.1207	7.305	10.387	7.305	10.387	7.305	10.162302	7.239582
r	4	4.555	4	3.546	4	3.546	4.556	3.546	4.556	3.546	4.277858	3.713758
N_c	10	9	10	11	10	11	9	11	9	11	9	11
$Q_{c,c}$ (W)	2.123	–	2.2614	1.6947	2.273	1.6947	2.276	1.6947	2.276	1.6947	**2.290888**	1.717034
COP	–	0.048	0.0398	0.0506	0.0374	0.0506	0.0354	0.0506	0.0354	0.0506	0.037107	**0.051153**

1.498%, 1.323%, 1.323%, 1.323 and 4.256% as compared to the results of GA [14], PSO, ABC, TLBO, modified-TLBO [19] and CRO [20] algorithms.

Table 2 presents the results obtained by using MO-SAMP Jaya algorithm and their comparison for the design optimization two-stage electrically connected TEC. Table shows the comparison of results for single objective optimization. It can be observed from this table that the results obtained by using MO-SAMP Jaya algorithm are better as compared to the results of GA [14], PSO, ABC, TLBO, modified-TLBO [19] and CRO [20] algorithms for each value of RS_t. When the value of $RS_t = 0.02$ cm^2 K/W is considered, the value of COP obtained by MO-SAMP Jaya algorithm is increased by 3.45%, 2.94%, 2.94%, 2.94% and 2.94% as compared to the results of PSO, ABC, TLBO and modified-TLBO [19] algorithms. Subsequently, the value cooling capacity is increased by 2.81%, 0.435%, 0.435%, 0.435% and 0.355% as compared to the results of GA [14], PSO, ABC, TLBO and modified-TLBO [19] algorithms.

When the value of $RS_t = 0.2$ cm^2 K/W is considered, the value of COP obtained by MO-SAMP Jaya algorithm is increased by 9.735%, 3.867%, 3.867%, 2.965% and 2.965% as compared to the results of GA [14], PSO, ABC, TLBO and modified-TLBO [19] algorithms. Subsequently, the value cooling capacity is increased by 3.39%, 1.64%, 1.524%, 1.524% and 1.524% as compared to the results of GA [14], PSO, ABC, TLBO and modified-TLBO [19] algorithms. When the value of $RS_t = 2$ cm^2 K/W is considered, the value of COP obtained by MO-SAMP Jaya algorithm is increased by 6.16%, 1.08%, 1.08%, 1.08% and 1.08% as compared to the results of GA [14], PSO, ABC, TLBO and modified-TLBO [19] algorithms. Subsequently, the value cooling capacity is increased by 3.39%, 1.287%, 0.780%, 0.6498% and 0.6498% as compared to the results of GA [14], PSO, ABC, TLBO and modified-TLBO [19] algorithms.

Table 3 presents the specification of sample design points obtained by MO-SAMP Jaya algorithm and its comparison with modified-TLBO for the thermal performance optimization of two-stage electrically separated TEC. It can be observed from this table that results obtained by using MO-SAMP Jaya algorithm is better at each design point with respect to both the objective as compared to the design points suggested by modified-TLBO.

Fig. 7 presents the distribution of Pareto optimal curve obtained by MO-SAMP Jaya algorithm and its comparison with modified-TLBO for electrically separated TEC with different values of RS_t. It can be observed from this figure that the Pareto optimal solutions are uniformly distributed and clearly showing the conflicting nature of COP and cooling capacity for TEC. Furthermore, it can also be observed that the Pareto optimal solutions obtained by MO-SAMP Jaya algorithm are dominating the Pareto optimal solutions suggested by modified-TLBO for each value of RS_t.

Table 4 presents the specification of sample design points obtained by MO-SAMP Jaya algorithm and its comparison with the modified-TLBO for design optimization of two-stage electrically connected TEC. Table shows the comparison of results for multiobjective optimization. It can be observed from this table that results obtained by using MO-SAMP Jaya algorithm is better at each design point with respect to both the objective as compared to the design points suggested by modified-TLBO. Fig. 8 presents the distribution

TABLE 3. Optimal output variables for a to e Pareto optimal front shown in Figure 3.

Output variable	Design point									
	A		**B**		**C**		**D**		**E**	
RS_j= 0.02cm^2/KW										
	Modified-TLBO [19]	MO-SAMP Jaya	Modified-TLBO [19]	MO-SAMP Jaya	Modified-TLBO [19]	MO-SAMP Jaya	Modified-TLBO [19]	MO-SAMP Jaya	Modified-TLBO [19]	MO-SAMP Jaya
I_h (A)	6.7299	6.80538	7.4285	7.34708	8.0476	7.99578	8.7347	8.58389	9.3077	9.13323
I_c(A)	7.581	7.23250	7.4018	7.33201	7.5229	7.16217	7.6351	7.22088	7.7146	7.44642
r	6.143	5.87360	5.25	5.50324	5.25	5.32409	5.25	5.26368	5.25	5.29626
N_c	7		8		8		8		8	
$Q_{c,c}$ (W)	0.5968	**0.61851**	0.6788	**0.68766**	0.7375	**0.74620**	0.7745	**0.77809**	0.784	**0.78880**
COP	0.0192	**0.01938**	0.0189	**0.01914**	0.018	**0.01813**	0.0165	**0.01681**	0.015	**0.01532**
RS_j= 0.2cm^2/KW										
	Modified-TLBO	MO-SAMP Jaya	Modified-TLBO	MO-SAMP Jaya	Modified-TLBO	MO-SAMP Jaya	Modified-TLBO	MO-SAMP Jaya	Modified-TLBO	MO-SAMP Jaya
I_h (A)	6.5338	6.71639	7.0084	7.09158	7.5076	7.54155	8.0907	8.18007	9.3278	9.35051
I_c(A)	7.8165	7.28610	7.5756	7.26253	7.6925	7.20519	7.8118	7.25475	8.0121	7.51670
r	6.143	5.71820	5.25	5.37315	5.25	5.35857	5.25	4.92489	5.25	5.02678
N_c	7		8		8		8		8	
$Q_{c,c}$ (W)	0.6544	0.68259	0.717	0.73706	0.782	0.79337	0.8368	0.85187	0.8826	0.89600
COP	0.0219	0.02228	0.0217	0.02214	0.0212	0.02161	0.0201	0.02045	0.0168	0.01715
RS_j= 0.2cm^2/KW										
	Modified-TLBO	MO-SAMP Jaya	Modified-TLBO	MO-SAMP Jaya	Modified-TLBO	MO-SAMP Jaya	Modified-TLBO	MO-SAMP Jaya	Modified-TLBO	MO-SAMP Jaya
I_h (A)	4.4163	4.549142	5.5156	5.483569	6.9828	7.032462	7.9011	7.833480	9.609	9.625534
I_c(A)	10.722	10.911666	10.759	10.901168	10.866	10.919350	10.581	10.876827	11	11.000000
r	7.333	7.330000	6.143	6.195861	5.25	5.186034	4.556	4.881261	4.556	4.614992
N_c	6		7		8		9		9	
$Q_{c,c}$ (W)	1.201	**1.249334**	1.5826	**1.586952**	1.9754	**2.011373**	2.1289	**2.153943**	2.254	**2.284225**
COP	0.0654	**0.065771**	0.0631	**0.063862**	0.0559	**0.056329**	0.0506	**0.051445**	0.0393	**0.039678**

TABLE 4. Optimal output variables for A to E Pareto optimal front shown in Figure 4.

Output variable	Design point									
	A		**B**		**C**		**D**		**E**	
RS_j= 0.02cm^2/KW										
	Modified-TLBO [19]	MO-SAMP Jaya	Modified-TLBO [19]	MO-SAMP Jaya	Modified-TLBO [19]	MO-SAMP Jaya	Modified-TLBO [19]	MO-SAMP Jaya	Modified-TLBO [19]	MO-SAMP Jaya
I_h (A)	7.1558	11.00000	7.4227	11.00000	7.7519	11.00000	8.002	11.00000	8.5737	11.00000
I_c(A)	7.1558	6.99632	7.4227	7.33878	7.7519	7.68009	7.6351	7.93147	8.5737	8.36134
r	5.25	5.56300	5.25	5.59720	5.25	5.62531	5.25	5.85668	6.143	6.09197
N_c	8		8		8		8		7	
$Q_{c,c}$ (W)	0.6405	0.64292	0.6785	0.69136	0.7127	0.72461	0.7294	0.74105	0.7479	0.75117
COP	0.0191	0.01968	0.0189	0.01944	0.0184	0.01879	0.0178	0.01810	0.0159	0.01666
RS_j= 0.2cm^2/KW										
	Modified-TLBO	MO-SAMP Jaya	Modified-TLBO	MO-SAMP Jaya	Modified-TLBO	MO-SAMP Jaya	Modified-TLBO	MO-SAMP Jaya	Modified-TLBO	MO-SAMP Jaya
I_h (A)	7.1681	4.000000	7.4634	4.000000	7.7568	9.322877	8.223	11.000000	8.7375	8.016163
I_c(A)	7.1681	6.992917	7.4634	7.409904	7.7568	7.723920	8.223	8.157521	8.7375	8.475959
r	6.143	5.316666	5.25	5.489646	5.25	5.572283	5.25	5.675717	6.143	5.837901
N_c	8		8		8		8		7	
$Q_{c,c}$ (W)	0.7098	0.716019	0.7563	0.781089	0.7915	0.814710	0.825	0.841147	0.8338	0.846712
COP	0.0215	0.022157	0.0209	0.021763	0.0204	0.021067	0.0191	0.019718	0.0172	0.018511
RS_j= 2cm^2/KW										
	Modified-TLBO	MO-SAMP Jaya	Modified-TLBO	MO-SAMP Jaya	Modified-TLBO	MO-SAMP Jaya	Modified-TLBO	MO-SAMP Jaya	Modified-TLBO	MO-SAMP Jaya
I_h (A)	7.305	6.270143	7.77	5.891394	8.285	6.028879	9.32	6.552738	10.387	4.000000
I_c(A)	7.305	7.239582	7.77	7.760746	8.285	8.223616	9.32	9.252285	10.387	10.162302
r	3.546	3.713758	3.546	3.714130	3.546	3.681142	4	3.985238	4.556	4.277858
N_c	11		11		11		10		9	
$Q_{c,c}$ (W)	1.6947	1.717034	1.868	1.910634	2.02	2.043366	2.2258	2.240121	2.276	2.290888
COP	0.0506	0.051153	0.0499	0.050397	0.0481	0.048739	0.0426	0.043095	0.0354	0.037107

of Pareto optimal curve obtained by MO-SAMP Jaya algorithm and comparison for electrically connected TEC with values of RS_t.

B. TWO STAGE IRREVERSIBLE HEAT PUMP

Table 5 presents the set of nondominated solutions obtained by using MO-SAMP Jaya algorithm for multiobjective

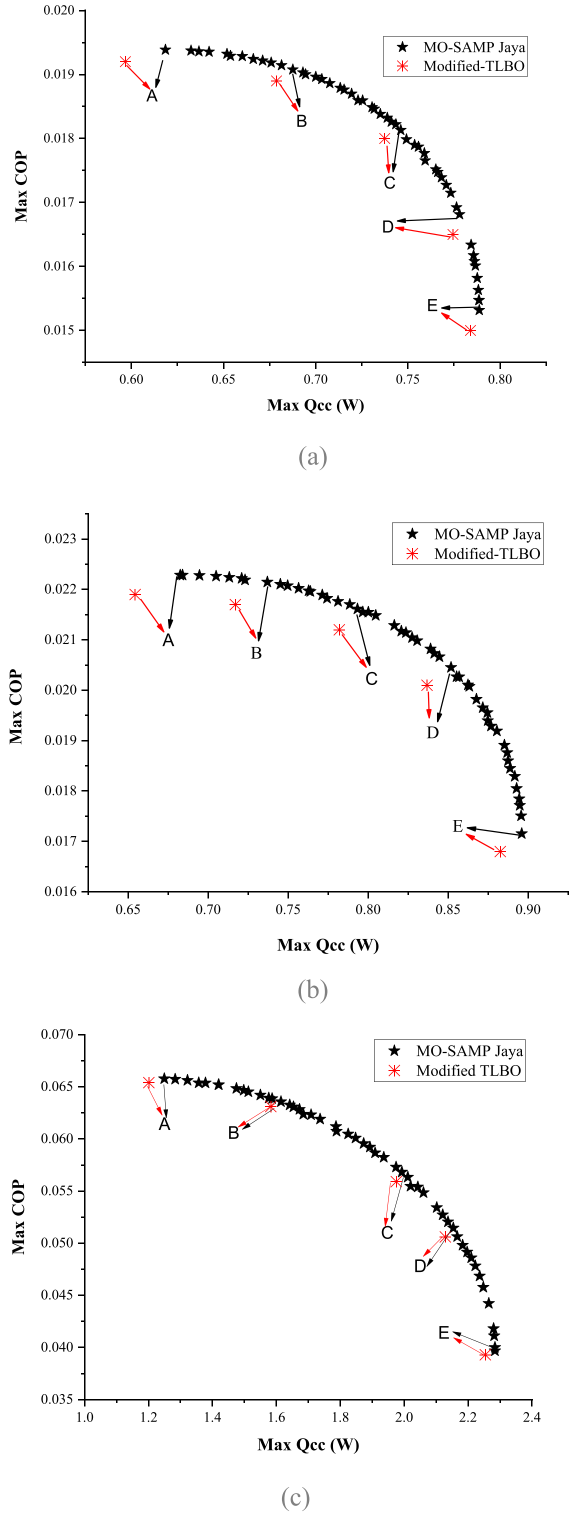

FIGURE 7. The distribution of Pareto-optimal points solutions for electrically separated TEC using the modified TLBO algorithm and MOSAMP Jaya algorithm (a) RSj = 0.02 cm^2 K/W, (b) RSj=0.2 cm^2 K/W, and (c) RS=2 cm^2 K/W.

optimization of irreversible heat pump. A designer may select any solution based on the application requirement.

Fig. 9 presents the Pareto optimal curve obtained by using MO-SAMP Jaya algorithm for multiobjective optimization of two-stage irreversible heat pump.

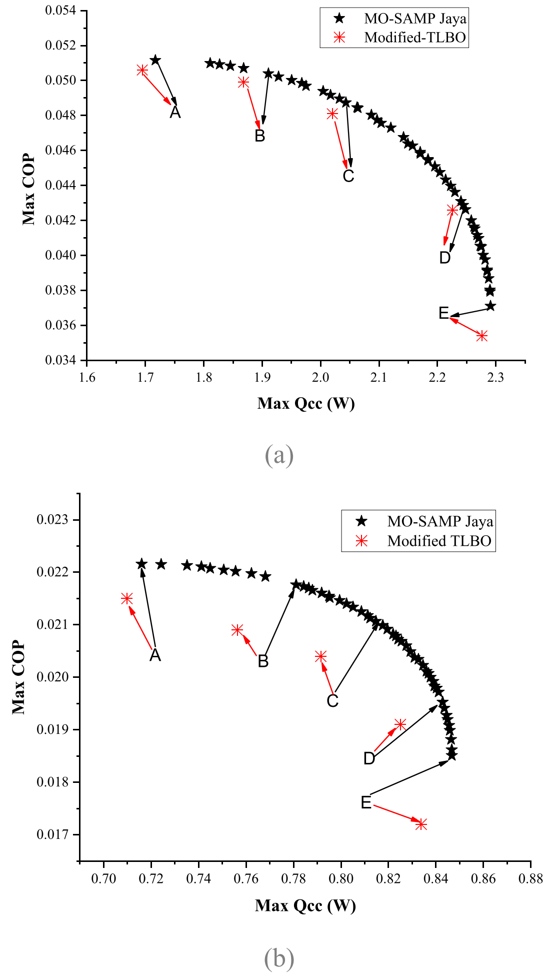

FIGURE 8. The distribution of Pareto-optimal points solutions for electrically connected TEC using the modified TLBO algorithm and MO-SAMP-Jaya algorithm (a) RSj = 0.02 cm^2 K/W, (b) RSj=0.2 cm^2 K/W.

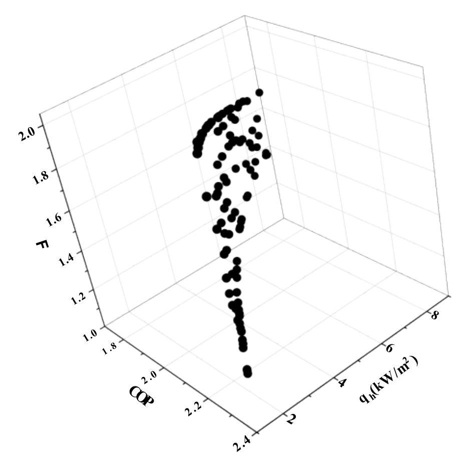

FIGURE 9. Pareto optimal curve for two-stage irreversible heat pump.

Table 6 presents the comparison of results obtained by MO-SAMP Jaya algorithm with other methods like TOPSIS, LINMAP and fuzzy logic which are based on the MO-GA algorithm. It is to be noted that the set

TABLE 5. Sets of nondominated solutions for two-stage irreversible heat pump.

S.No.	Tx (K)	Tz (K)	u	K	COP	Qh (kW/m^2)	F
1	4.12E+02	2.66E+02	9.72E-01	1.00E+00	2.27E+00	2.08E+00	1.08E+00
2	4.49E+02	2.50E+02	9.04E-01	1.00E-01	1.80E+00	8.17E+00	1.76E+00
3	4.16E+02	2.66E+02	9.70E-01	1.00E-01	2.24E+00	2.28E+00	2.04E+00
4	4.12E+02	2.66E+02	9.72E-01	1.82E-01	2.27E+00	2.08E+00	1.89E+00
5	4.49E+02	2.50E+02	9.19E-01	6.02E-01	1.83E+00	7.60E+00	1.60E+00
6	4.45E+02	2.50E+02	9.04E-01	1.00E+00	1.81E+00	7.89E+00	1.48E+00
7	4.41E+02	2.52E+02	9.22E-01	1.00E-01	1.88E+00	6.70E+00	1.83E+00
8	4.26E+02	2.55E+02	9.32E-01	1.00E-01	1.98E+00	5.11E+00	1.91E+00
9	4.31E+02	2.57E+02	9.42E-01	1.00E-01	1.99E+00	4.94E+00	1.92E+00
10	4.23E+02	2.62E+02	9.54E-01	1.00E+00	2.11E+00	3.57E+00	1.33E+00
11	4.26E+02	2.60E+02	9.53E-01	1.00E+00	2.08E+00	3.93E+00	1.36E+00
12	4.39E+02	2.51E+02	9.04E-01	7.09E-01	1.84E+00	7.33E+00	1.56E+00
13	4.37E+02	2.51E+02	9.04E-01	1.00E-01	1.86E+00	7.04E+00	1.81E+00
14	4.39E+02	2.55E+02	9.04E-01	1.00E+00	1.87E+00	6.80E+00	1.47E+00
15	4.49E+02	2.55E+02	9.04E-01	4.68E-01	1.84E+00	7.32E+00	1.64E+00
16	4.33E+02	2.56E+02	9.19E-01	1.00E+00	1.93E+00	5.87E+00	1.45E+00
17	4.31E+02	2.60E+02	9.54E-01	1.00E-01	2.05E+00	4.21E+00	1.95E+00
18	4.49E+02	2.50E+02	9.31E-01	6.55E-01	1.85E+00	7.10E+00	1.58E+00
19	4.35E+02	2.55E+02	9.30E-01	1.00E-01	1.94E+00	5.77E+00	1.87E+00
20	4.30E+02	2.56E+02	9.36E-01	1.00E+00	1.99E+00	5.09E+00	1.43E+00
21	4.44E+02	2.53E+02	9.28E-01	1.26E-01	1.88E+00	6.58E+00	1.82E+00
22	4.34E+02	2.56E+02	9.38E-01	3.33E-01	1.97E+00	5.31E+00	1.75E+00
23	4.31E+02	2.56E+02	9.23E-01	2.78E-01	1.95E+00	5.60E+00	1.78E+00
24	4.14E+02	2.64E+02	9.66E-01	1.00E+00	2.22E+00	2.45E+00	1.17E+00
25	4.24E+02	2.61E+02	9.40E-01	1.00E-01	2.07E+00	4.02E+00	1.97E+00
26	4.19E+02	2.64E+02	9.66E-01	1.00E+00	2.19E+00	2.75E+00	1.22E+00
27	4.25E+02	2.60E+02	9.44E-01	1.00E-01	2.06E+00	4.14E+00	1.96E+00
28	4.27E+02	2.57E+02	9.35E-01	1.00E+00	2.00E+00	4.84E+00	1.42E+00
29	4.44E+02	2.50E+02	9.09E-01	3.82E-01	1.83E+00	7.69E+00	1.67E+00
30	4.16E+02	2.65E+02	9.65E-01	1.00E+00	2.22E+00	2.51E+00	1.18E+00
31	4.44E+02	2.50E+02	9.04E-01	9.79E-01	1.82E+00	7.79E+00	1.48E+00
32	4.36E+02	2.54E+02	9.45E-01	1.77E-01	1.96E+00	5.34E+00	1.84E+00
33	4.35E+02	2.57E+02	9.23E-01	3.47E-01	1.94E+00	5.67E+00	1.74E+00
34	4.32E+02	2.54E+02	9.34E-01	5.61E-01	1.95E+00	5.49E+00	1.63E+00
35	4.33E+02	2.55E+02	9.16E-01	3.70E-01	1.92E+00	5.98E+00	1.72E+00
36	4.45E+02	2.53E+02	9.17E-01	8.42E-01	1.86E+00	6.99E+00	1.52E+00
37	4.44E+02	2.52E+02	9.24E-01	5.53E-01	1.87E+00	6.88E+00	1.62E+00
38	4.19E+02	2.64E+02	9.66E-01	8.50E-01	2.19E+00	2.70E+00	1.30E+00
39	4.30E+02	2.56E+02	9.39E-01	1.00E+00	1.99E+00	5.01E+00	1.42E+00
40	4.41E+02	2.52E+02	9.04E-01	1.18E-01	1.85E+00	7.28E+00	1.79E+00
41	4.27E+02	2.54E+02	9.24E-01	1.00E-01	1.95E+00	5.46E+00	1.88E+00
42	4.27E+02	2.60E+02	9.35E-01	4.89E-01	2.02E+00	4.56E+00	1.66E+00
43	4.45E+02	2.56E+02	9.29E-01	2.08E-01	1.90E+00	6.26E+00	1.79E+00
44	4.24E+02	2.60E+02	9.54E-01	1.00E-01	2.09E+00	3.82E+00	1.98E+00
45	4.15E+02	2.66E+02	9.65E-01	1.00E+00	2.23E+00	2.40E+00	1.15E+00
46	4.19E+02	2.63E+02	9.44E-01	1.00E-01	2.12E+00	3.43E+00	1.99E+00
47	4.27E+02	2.57E+02	9.47E-01	4.32E-01	2.03E+00	4.42E+00	1.70E+00
48	4.23E+02	2.62E+02	9.63E-01	6.36E-01	2.14E+00	3.21E+00	1.50E+00
49	4.40E+02	2.52E+02	9.32E-01	7.03E-01	1.90E+00	6.36E+00	1.57E+00
50	4.30E+02	2.58E+02	9.38E-01	5.27E-01	2.00E+00	4.88E+00	1.63E+00

TABLE 6. Comparison of results for irreversible heat pump.

Method	Tx (K)	Tz (K)	u	K	COP	q_h (kW/m^2)	F	Z	Rank
TOPSIS [22]	447.340	251.110	0.911	0.251	1.828	7.640	1.724	0.915	2
LINMAP [22]	441.754	250.437	0.917	0.202	1.854	7.144	1.762	0.904	3
Fuzzy logic [22]	428.853	257.901	0.940	0.221	2.011	4.734	1.839	0.836	4
MO-SAMP Jaya	448.800	249.600	0.904	0.100	1.802	8.168	1.763	**0.941**	**1**

of nondominated solutions obtained by MO-SAMP Jaya algorithm are not found superior with respect to all objectives as compared to other methods used by previous researchers. Therefore, a well known multi-attribute decision making method known as weighted sum method [9] is used for selecting the best solution. In this, a normalized score is calculated for each method by considering equal weights of each objective which are same as used by

TABLE 7. Sets of nondominated solutions for PFHE design.

S.No.	L_h (m)	L_c (m)	b (m)	t_f (m)	n (m^{-1})	x (m)	Np	C_{tot} ($)	A_{tot} (m^2)	O(x)	ε
1	0.99741	1.00000	0.00481	0.00010	395.28	0.00795	141	1139.83	1332.32	0.168	0.884
2	0.50378	0.32816	0.00481	0.00010	517.53	0.00453	141	1796.29	274.66	0.413	0.821
3	0.22603	0.19959	0.00481	0.00010	1000.00	0.00227	141	5527.10	132.92	1.489	0.826
4	0.98774	0.80450	0.00481	0.00010	1000.00	0.00236	141	4550.79	2341.32	1.027	0.943
5	1.00000	0.86407	0.00481	0.00010	1000.00	0.00685	141	3319.73	2545.88	0.690	0.939
6	0.69824	0.74735	0.01	0.00010	255.93	0.003382	71	967.84	450.71	0.114	0.821
7	0.62133	0.82815	0.00481	0.00010	399.20	0.00784	141	999.87	692.70	0.191	0.854
8	1.00000	0.49223	0.00481	0.00010	1000.00	0.00494	141	5078.42	1450.31	1.134	0.923
9	0.30413	0.99755	0.00481	0.00010	719.31	0.00572	141	3003.34	667.08	0.920	0.878
10	0.57734	0.58431	0.00481	0.00010	431.95	0.00458	141	1203.23	483.57	0.257	0.846
11	0.42559	0.29541	0.00481	0.00010	1000.00	0.00506	141	4299.86	370.43	1.067	0.870
12	0.49324	0.35620	0.00481	0.00010	1000.00	0.00213	141	5440.86	517.67	1.362	0.893
13	1.00000	0.91939	0.00481	0.00010	796.21	0.00811	141	2330.52	2209.86	0.442	0.926
14	0.20532	0.30350	0.00481	0.00010	1000.00	0.00601	141	3543.06	183.60	1.046	0.832
15	0.25587	0.31076	0.00481	0.00010	1000.00	0.00226	141	4776.57	234.28	1.360	0.858
16	0.23274	0.32735	0.00481	0.00010	955.29	0.00532	141	3337.08	215.41	0.967	0.840
17	1.00000	1.00000	0.00481	0.00010	680.17	0.00383	141	2263.06	2094.56	0.438	0.925
18	0.45315	0.25975	0.00481	0.00010	1000.00	0.00511	141	4938.56	346.80	1.204	0.867
19	0.99316	0.82509	0.00481	0.00010	1000.00	0.00347	141	4027.88	2414.42	0.884	0.942
20	1.00000	0.77034	0.00481	0.00010	879.97	0.00693	141	2892.57	2023.47	0.588	0.928
21	1.00000	0.54828	0.00481	0.00010	663.99	0.00605	141	2485.56	1124.78	0.507	0.897
22	0.87965	0.34698	0.00481	0.00010	913.15	0.00804	141	4731.81	828.70	1.069	0.895
23	0.57417	0.88495	0.00481	0.00010	781.11	0.00670	141	2199.24	1200.87	0.526	0.906
24	0.22423	0.22664	0.00481	0.00010	1000.00	0.00349	141	4430.04	149.74	1.218	0.827
25	0.52146	0.76799	0.00481	0.00010	1000.00	0.00654	141	3091.34	1179.96	0.799	0.915
26	0.96373	0.97140	0.00481	0.00010	657.74	0.00653	141	1915.61	1904.93	0.351	0.917
27	1.00000	0.86825	0.00481	0.00010	874.04	0.00742	141	2709.47	2266.93	0.538	0.931
28	0.52956	0.83296	0.00481	0.00010	789.10	0.00515	141	2386.10	1051.88	0.600	0.903
29	1.00000	0.84350	0.00481	0.00010	1000.00	0.00741	141	3280.53	2485.29	0.679	0.938
30	0.77697	0.88539	0.00481	0.00010	403.31	0.00778	141	1063.88	933.62	0.181	0.869
31	0.34672	0.84272	0.00481	0.00010	886.51	0.00394	141	3676.11	772.58	1.109	0.898
32	0.99793	0.35784	0.00481	0.00010	524.88	0.00597	141	2610.14	600.27	0.558	0.860
33	0.37801	0.32965	0.00481	0.00010	980.02	0.00699	141	3330.76	360.51	0.848	0.865
34	0.99902	0.95277	0.00481	0.00010	410.82	0.00798	141	1175.90	1310.84	0.177	0.884
35	0.43235	0.40993	0.00481	0.00010	1000.00	0.00214	141	4754.30	522.19	1.245	0.894
36	0.36974	0.49088	0.00481	0.00010	1000.00	0.00411	141	3623.18	534.78	1.000	0.888
37	1.00000	0.59425	0.00481	0.00010	849.89	0.00534	141	3387.62	1513.33	0.720	0.919
38	0.94180	1.00000	0.00481	0.00010	675.36	0.00562	141	2021.10	1960.58	0.382	0.920
39	0.72999	0.83698	0.00481	0.00010	1000.00	0.00275	141	3937.98	1800.22	0.960	0.935
40	0.99750	0.79486	0.00481	0.00010	1000.00	0.00600	141	3534.46	2336.13	0.748	0.938
41	0.55683	0.99242	0.00481	0.00010	826.01	0.00527	141	2616.91	1372.13	0.663	0.914
42	1.00000	0.62081	0.00481	0.00010	839.77	0.00422	141	3457.19	1564.22	0.740	0.921
43	0.94162	0.89588	0.00481	0.00010	908.39	0.00439	141	3150.49	2279.70	0.671	0.936
44	0.65537	0.66442	0.00481	0.00010	407.80	0.00649	141	1065.43	596.17	0.207	0.850
45	1.00000	0.77511	0.00481	0.00010	855.60	0.00669	141	2802.79	1985.69	0.566	0.927
46	1.00000	0.91225	0.00481	0.00010	518.59	0.00798	141	1460.47	1518.19	0.241	0.898
47	0.99973	0.95711	0.00481	0.00010	536.00	0.00770	141	1514.69	1636.77	0.251	0.903
48	0.48928	0.35110	0.00481	0.00010	526.00	0.00489	141	1685.51	289.28	0.389	0.824
49	0.99782	0.96679	0.00481	0.00010	616.69	0.00805	141	1731.97	1857.49	0.299	0.912
50	0.42640	0.80374	0.00481	0.00010	1000.00	0.00429	141	3745.47	1009.78	1.067	0.912

TABLE 8. Multiobjective optimization results of MO-SAMP JAYA algorithm.

Parameters	Value
L_h (m)	0.69824
L_c (m)	0.74735
b (m)	0.01
t_f (m)	0.00015387
n (m^{-1})	255.93
x (m)	0.003382
Np	71
D_h (mm)	5.2518
G_c (kg/(m^2s))	4.2061
Re_h	433.18
Re_c	657.42
f_h	0.1164
f_c	0.087775
ΔP_h (kPa)	0.53782
ΔP_c (kPa)	0.45855
j_h	0.023993
h_h (W/(m^2K))	109.73
j_c	0.019836
h_c (W/(m^2K))	114.21
ε	0.82055
A_h (m^2)	223.78
A_c (m^2)	226.93
A_t (m^2)	450.71
C_{in} ($/year)	572.91
C_{op} ($/year)	394.93
C_{tot} ($/year)	967.84
$O(x)$	0.11393

previous researchers. The normalized score (Z) is shown in Table 6.

It can be observed from Table 6 that the results obtained by MO-SAMP Jaya algorithm have obtained highest score among all four methods. Hence, MO-SAMP Jaya algorithm has given rank 1. Similarly, TOPSIS, LINMAP and Fuzzy logic methods get the 2nd, 3rd, and 4th ranks. It can be concluded based on the rank of the solutions that the MO-SAMP Jaya algorithm has performed better for multiobjective optimization of irreversible heat pump as compared to the NSGA [22].

C. PLATE-FIN HEAT EXCHANGER

In this work conflicting objectives namely minimization of the total cost (annual investment cost and operational cost), total surface area, total pressure drop and maximization of heat exchanger effectiveness are optimized simultaneously. The sets of nondominated solutions obtained by MO-SAMP Jaya algorithm are given in Table 7.

As, the multiobjective design optimization is not carried out by the previous researchers. Hence, the results cannot be compared. The best compromise solution obtained by MO-SAMP Jaya algorithm is presented in Table 8.

D. TRANSCRITICAL CYCLES

1) OPTIMIZATION OF A MODIFIED TRANSCRITICAL CO_2 REFRIGERATION CYCLE

Table 9 presents the set of nondominated solutions obtained by MO-SAMP Jaya algorithm for the multiobjective design optimization of modified CO_2 refrigeration cycle with the objectives of maximization of cooling rate and minimization of total cost.

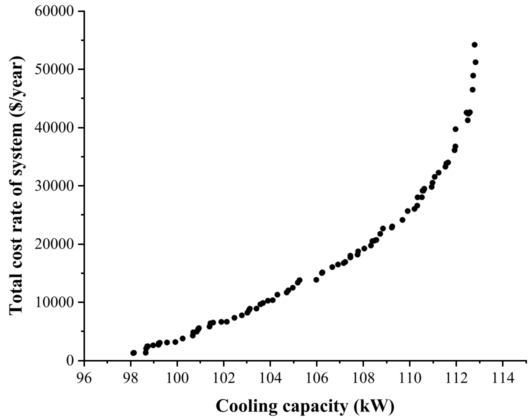

FIGURE 10. Pareto optimal curve for refrigeration TC cycle.

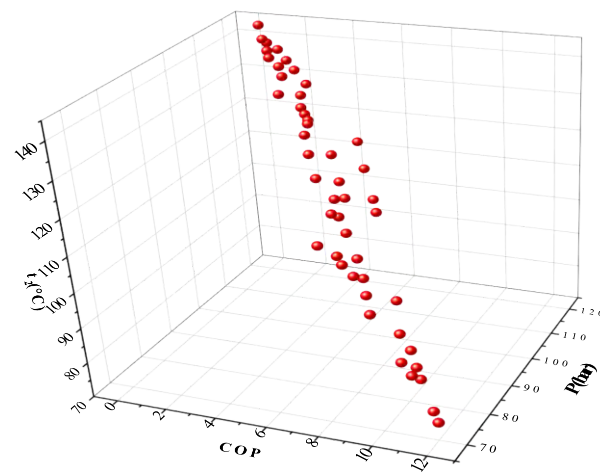

FIGURE 11. Pareto optimal curve obtained by MO-SAMP-Jaya algorithm for TC heat pump cycle.

The comparison of results obtained by MO-SAMP Jaya algorithm with multiobjective genetic algorithm (MO-GA) is shown in Table 10.

It can be observed from Table 10 that the results obtained by MO-SAMP Jaya algorithm are found better as compared to the results of MO-GA with respect to all design points. Fig. 10 presents the Pareto optimal curves obtained by Jaya algorithm and its improved versions with a priori approach, MO-SAMP Jaya algorithm and the comparison with the results of MO-GA which show the superiority of design obtained by MO-SAMP Jaya as compared to MO-GA [37].

2) OPTIMIZATION OF TRANSCRITICAL CO_2 HEAT PUMP CYCLE

Table 11 presents the sets of nondominated solutions for TC CO_2 heat pump cycle for simultaneous heating and cooling applications. Fig. 11 presents the Pareto optimal

TABLE 9. Sets of nondominated solutions for refrigeration cycle.

S.No.	Pgc (bar)	Tgc (°C)	Te (°C)	α	$q_{cooling}$ (kW)	Cost ($/year)
1	125.46	35.00	-23.08	0.26	112.83	51211.66
2	110.65	35.00	-24.25	0.31	112.70	46479.25
3	131.30	35.00	-20.51	0.35	111.97	39707.91
4	114.09	35.01	-22.02	0.26	112.73	48899.33
5	114.15	35.00	-23.38	0.33	112.59	42618.78
6	108.73	35.00	-22.35	0.50	109.69	24140.80
7	118.17	35.04	-21.55	0.38	111.96	36751.03
8	110.87	35.00	-22.38	0.34	112.49	41233.66
9	117.56	35.00	-21.61	0.38	111.93	36097.51
10	109.58	35.00	-23.61	0.41	111.65	33992.19
11	104.34	35.00	-22.31	0.61	105.98	13850.44
12	104.70	35.09	-20.93	0.47	109.91	25659.26
13	105.49	35.06	-23.42	0.42	111.24	32246.42
14	109.26	35.19	-22.08	0.52	108.73	21751.82
15	106.68	35.01	-19.68	0.58	106.67	16042.56
16	97.58	35.00	-23.74	0.71	100.24	3772.46
17	98.19	35.08	-21.45	0.63	104.31	11295.95
18	108.53	35.00	-22.41	0.48	110.32	26586.71
19	114.93	35.00	-24.14	0.44	111.07	31528.47
20	103.65	35.00	-24.06	0.68	102.46	7332.79
21	110.08	35.04	-23.25	0.42	111.53	33263.64
22	103.68	35.00	-24.24	0.57	107.45	17710.43
23	111.88	35.00	-21.10	0.51	109.25	23013.16
24	104.67	35.22	-23.75	0.62	104.97	12490.20
25	105.75	35.08	-21.24	0.42	110.98	30524.66
26	105.23	35.05	-20.56	0.54	108.05	19220.63
27	101.92	35.00	-19.21	0.49	108.85	22653.59
28	104.83	35.00	-21.11	0.54	108.33	19735.26
29	100.33	35.00	-25.28	0.70	100.67	4271.52
30	104.93	35.21	-22.29	0.46	110.34	28010.92
31	99.74	35.00	-18.92	0.60	105.19	13367.37
32	101.01	35.00	-25.08	0.67	102.78	7766.61
33	106.78	35.38	-20.88	0.61	105.26	13789.07
34	104.00	35.19	-20.84	0.59	106.25	15132.49
35	99.12	35.00	-26.28	0.71	99.92	3168.01
36	99.63	35.02	-23.78	0.59	106.23	15018.00
37	101.05	35.00	-25.30	0.64	104.11	10357.47
38	104.34	35.00	-25.27	0.69	101.40	5823.49
39	108.12	35.00	-20.50	0.43	110.94	29801.69
40	107.40	35.00	-21.68	0.48	110.20	26030.15
41	99.06	35.00	-23.72	0.68	102.14	6646.44
42	102.91	35.00	-22.26	0.56	107.76	18168.30
43	97.83	35.00	-24.84	0.73	98.65	1328.48
44	104.24	35.00	-20.23	0.52	108.57	20694.16
45	99.23	35.00	-30.00	0.73	98.12	1274.13
46	104.61	35.00	-24.34	0.46	110.59	29162.56
47	99.16	35.16	-22.24	0.72	99.21	2956.08
48	116.34	35.02	-23.31	0.34	112.55	42430.81
49	97.92	35.03	-27.81	0.69	100.91	5427.68
50	122.42	35.00	-23.12	0.23	112.79	54204.21

TABLE 10. Comparison of multiobjective optimization results of refrigeration cycle.

Design point	Algorithm	Pgc (bar)	Tgc (°C)	Te (°C)	α	$q_{cooling}$ (kW)	Cost ($/year)
A	MO-GA [37]	104.73	35.02	-3.43	0.80	87.25	6466.40
	MO-SAMP Jaya	99.23	35.00	-30.00	0.73	98.12	1274.13
B	MO-GA [37]	117.56	35.03	-9.23	0.52	102.29	17036.00
	MO-SAMP Jaya	104.34	35.00	-22.31	0.61	105.98	13850.44
C	MO-GA [37]	117.95	35.01	-9.61	0.14	104.94	40616.00
	MO-SAMP Jaya	104.61	35.00	-24.34	0.46	110.59	29162.56

curve obtained by MO-SAMP Jaya algorithm for heat pump cycle. As the previous researchers did not present any multi-objective optimization results, therefore, comparison with the previous results cannot be made.

A designer may choose any solution as per the requirement from Table 11.

E. IRREVERSIBLE CARNOT POWER CYCLE

Table 12 presents the sets of Pareto optimal solutions obtained by using MO-SAMP Jaya algorithm.

The results obtained by MO-SAMP Jaya algorithm and the comparison with the results obtained by TOPSIS, LINMAP, and fuzzy logic methods (these methods have used

TABLE 11. Sets of nondominated solutions for heat pump cycle.

S.No.	tev (°C)	t3 (°C)	COP	P (bar)	t2 (°C)
1	10.000	30.000	11.750	72.680	72.330
2	-10.000	48.500	0.466	120.721	143.758
3	-10.000	48.500	0.466	120.721	143.758
4	10.000	30.000	11.750	72.680	72.330
5	-4.198	41.284	4.278	102.159	119.565
6	-4.260	42.665	3.793	105.517	122.700
7	8.325	34.473	9.384	83.631	85.951
8	-6.962	45.862	2.104	113.754	133.627
9	2.198	42.144	5.327	103.154	112.140
10	0.197	38.840	6.045	95.507	107.521
11	-10.000	47.304	0.931	117.794	141.391
12	10.000	37.110	8.723	89.674	90.235
13	10.000	33.064	10.322	79.980	80.280
14	-3.717	45.023	3.086	111.158	126.905
15	0.045	39.986	5.614	98.299	110.374
16	1.174	38.154	6.493	93.687	104.526
17	-3.091	44.802	3.296	110.514	125.503
18	-7.220	46.531	1.805	115.431	135.399
19	-2.862	35.033	6.811	86.876	102.897
20	-0.449	48.500	2.472	119.097	129.106
21	-8.874	43.484	2.542	108.290	131.659
22	1.625	43.888	4.607	107.488	116.719
23	-9.459	46.639	1.294	116.077	139.179
24	10.000	48.500	4.666	117.321	114.958
25	2.433	36.980	7.182	90.648	99.974
26	10.000	43.106	6.636	104.162	103.857
27	10.000	30.603	11.451	74.113	73.921
28	5.896	31.966	9.946	78.057	82.793
29	-8.893	47.607	1.047	118.347	140.215
30	-1.559	38.299	5.867	94.502	108.812
31	10.000	44.051	6.309	106.460	105.882
32	2.158	34.564	8.052	84.898	94.476
33	2.724	35.838	7.671	87.857	96.817
34	10.000	32.383	10.621	78.352	78.542
35	10.000	34.066	9.901	82.373	82.802
36	9.628	46.220	5.457	111.807	110.869
37	-6.170	48.500	1.271	120.069	137.685
38	-2.994	46.346	2.760	114.261	128.549
39	-9.403	46.093	1.507	114.735	137.977
40	-3.595	39.845	4.898	98.577	115.411
41	2.753	41.199	5.767	100.772	109.276
42	-2.137	34.778	7.064	86.142	101.190
43	-2.816	48.500	1.975	119.499	132.584
44	-2.869	44.163	3.567	108.921	123.826
45	-2.579	44.587	3.479	109.904	124.289
46	-4.409	48.500	1.640	119.770	134.982
47	7.624	31.801	10.384	77.370	80.091
48	1.497	33.175	8.489	81.689	91.925
49	-7.590	33.722	6.350	84.541	106.888
50	0.151	34.976	7.466	86.227	98.344

the data obtained by MO-GA) are presented in Table 13. It can be observed from Table 13 that deviation index of the solution obtained by MO-SAMP Jaya algorithm is minimum

TABLE 12. Sets of Pareto optimal solutions given by MO-SAMP Jaya for irreversible Carnot cycle.

S.No.	x	y	z	EPC	η	MAW (kW)
1	0.6528	1.0000	1.8000	2.8656	0.3146	126.1631
2	0.4500	1.0000	1.8000	7.2499	0.5275	88.5056
3	0.4735	1.0000	1.8000	6.1564	0.5028	98.2047
4	0.4684	1.0000	1.8000	6.3681	0.5082	96.2344
5	0.4791	1.0000	1.8000	5.9465	0.4970	100.1987
6	0.4949	1.0000	1.8000	5.4156	0.4804	105.4047
7	0.4573	1.0000	1.8000	6.8701	0.5198	91.7382
8	0.4896	1.0000	1.8000	5.5807	0.4859	103.7638
9	0.6023	1.0000	1.8000	3.3740	0.3676	124.4165
10	0.4542	1.0000	1.8000	7.0271	0.5231	90.3845
11	0.4846	1.0000	1.8000	5.7493	0.4912	102.1080
12	0.5303	1.0000	1.8000	4.5149	0.4432	114.5034
13	0.5069	1.0000	1.8000	5.0721	0.4677	108.8642
14	0.4818	1.0000	1.8000	5.8455	0.4941	101.1729
15	0.5955	1.0000	1.8000	3.4555	0.3747	123.8962
16	0.4529	1.0000	1.8000	7.0934	0.5244	89.8205
17	0.4601	1.0000	1.8000	6.7358	0.5169	92.9170
18	0.5108	1.0000	1.8000	4.9690	0.4636	109.9099
19	0.5402	1.0000	1.8000	4.3141	0.4328	116.4930
20	0.5500	1.0000	1.8000	4.1323	0.4225	118.2471
21	0.4876	1.0000	1.8000	5.6484	0.4880	103.0965
22	0.5354	1.0000	1.8000	4.4097	0.4379	115.5515
23	0.5185	1.0000	1.8000	4.7805	0.4556	111.8232
24	0.5546	1.0000	1.8000	4.0521	0.4177	118.9996
25	0.4987	1.0000	1.8000	5.3008	0.4763	106.5551
26	0.5258	1.0000	1.8000	4.6122	0.4479	113.5255
27	0.4502	1.0000	1.8000	7.2375	0.5273	88.6094
28	0.4631	1.0000	1.8000	6.5964	0.5137	94.1586
29	0.5452	1.0000	1.8000	4.2201	0.4276	117.4074
30	0.6356	1.0000	1.8000	3.0203	0.3326	125.9721
31	0.6096	1.0000	1.8000	3.2887	0.3599	124.9054
32	0.5217	1.0000	1.8000	4.7059	0.4523	112.5794
33	0.5004	1.0000	1.8000	5.2532	0.4746	107.0339
34	0.4656	1.0000	1.8000	6.4877	0.5111	95.1406
35	0.5840	1.0000	1.8000	3.6055	0.3868	122.8215
36	0.5272	1.0000	1.8000	4.5824	0.4465	113.8255
37	0.5373	1.0000	1.8000	4.3705	0.4358	115.9385
38	0.5580	1.0000	1.8000	3.9947	0.4141	119.5293
39	0.6400	1.0000	1.8000	2.9795	0.3280	126.0573
40	0.5035	1.0000	1.8000	5.1639	0.4713	107.9350

as compared to the other solutions obtained by TOPSIS, LINMAP, and fuzzy logic. Hence, MO-SAMP Jaya algorithm has obtained 1^{st} rank with 0.1016 deviation index value.

Table 14 shows the computational time taken by the algorithm to get the Pareto optimal solution for different case studies.

It may be concluded, based on the results of multiobjective optimization of selected thermal devices ad cycles that the

TABLE 13. Comparison of results for irreversible Carnot power cycle.

Method	x	y	z	EPC	η	MAW (kW)	Deviation index from ideal solution (d)
Non-ideal solution	-	-	-	2.8656	0.3146	88.5056	1
TOPSIS [49]	0.4500	0.9960	1.8000	7.2480	0.5270	88.5090	0.895638
LINMAP [49]	0.4510	0.9970	1.8000	7.1790	0.5260	89.0920	0.894804
Fuzzy logic [49]	0.5040	0.9910	1.8000	5.1500	0.4700	108.0550	0.480832
MO-SAMP Jaya	0.6356	1.0000	1.8000	3.0203	0.3326	125.9721	0.101629
Ideal solution	-	-	-	7.2499	0.5275	126.1631	0

TABLE 14. Compuational time taken by MO-SAMP-Jaya.

Device/Cycle	Avg. time (sec)
TEC (electrically separated)	34.95
TEC (electrically connected)	33.35
Heat pump	29.10
PFHE	90.55
Transcritical cycle (Refrigeration)	84.91
Transcritical cycle (Heat pump)	29.35
Carnot power cycle	23.25

results obtained by MO-SAMP Jaya algorithm are better as compared to other algorithms.

V. CONCLUSIONS

This paper proposes *a posteriori* multiobjective version of Jaya algorithm named as MO-SAMP Jaya algorithm. The proposed algorithm is used for the design optimization of three selected thermal devices namely two-stage thermo electric cooler, two stage irreversible heat pump, and a plate-fin heat exchanger and two basic thermal cycles namely transcritical CO_2 cycle and irreversible Carnot power cycle. The results obtained by using MO-SAMP Jaya algorithm are compared with those obtained by using GA, PSO, ABC, TLBO, MO-TLBO and CRO algorithms for two stage thermoelectric cooler; TOPSIS, LINMAP and fuzzy logic (the results of which were based on the results of MO-GA) for two stage irreversible heat pump; MO-GA for transcritical CO_2 refrigeration cycle; and TOPSIS, LINMAP and fuzzy logic (the results of which were based on the results of MO-GA) for irreversible Carnot power cycle. The MO-SAMP Jaya algorithm is proved superior to other advanced optimization in terms of quality of solutions. Furthermore, the proposed MO-SAMP Jaya algorithm *a posteriori approach* has provided multiple Pareto optimal solutions in single simulation run as compared to the *a priori* approach.

The proposed MO-SAMP Jaya algorithm may be easily extended to solve the multiobjective optimization problems of other thermal devices and cycles where the problems are complex and having a number of design variables.

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