Improved Heat Exchanger Network Synthesis without Stream Splits Based on Comprehensive Learning Particle Swarm Optimizer

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ABSTRACT: In this paper, an improved heat exchanger network (HEN) synthesis method based on the comprehensive learning particle swarm optimizer algorithm (CLPSO) is proposed to synthesize HENs without stream splits. Compared with the standard particle swarm algorithm, CLPSO employs a novel learning strategy that preserves the diversity of the swarm to discourage premature convergence. However, while the algorithm's global exploration capability is enhanced, the local search capability decreases and the convergence speed becomes slow. In addition, the solution quality of CLPSO is largely determined by the randomly generated particles' best previous position (pbest) during initialization. Hence, the solution may be unstable due to different pbest. For the abovementioned considerations, this paper proposes a new HEN initialization and renovation method to improve the quality of pbest, reduce the initial cost, and retain the obtained optimization results as much as possible in the optimization process to speed up the convergence of the algorithm. Four typical cases are simulated to verify the effectiveness of the proposed method. This method only needs a single-level optimization algorithm to obtain high-quality solutions, which will give it a bright prospect in research and application.
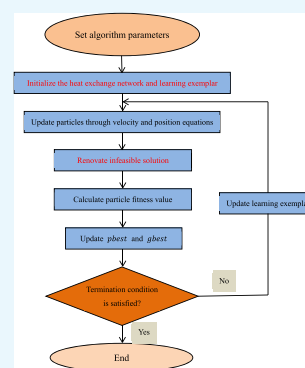
1. INTRODUCTION

Heat exchanger network (HEN) synthesis is one of the most active fields in chemical system engineering. The energy consumption of chemical production can be reduced by reasonably matching hot and cold process streams. However, it is usually a very complicated task to design a cost-effective HEN due to the combinatorial nature of the HEN synthesis problem. At present, the pinch method, mathematical programming methods, and metaheuristic methods have been widely applied in solving this problem.

The pinch method[1,2] is a sequential synthesis method. In this approach, performance targets for maximum process heat recovery, minimum number of exchangers, or exchanger area are first determined. Then, the network that most closely attains these targets through the identification of thermodynamic bottlenecks is determined.

The mathematical programming methods, taking into account energy consumption and investment costs, are capable of optimizing the global cost of the network. However, the computational difficulty remains as one of the challenges when applying mathematical programming approaches, especially for large-scale problems.[3] Recently, Chang et al.[4] introduced the concept of minimal structure (MSTR) and presented an enumeration algorithm to obtain globally optimal solutions. Nemet et al.[5] focused on synthesizing large-scale HENs using a two-step mathematical programming approach to achieve near globally optimal solutions. For the complex heat transfer network synthesis, considering the detailed design of heat exchangers, Short et al.[6] proposed a two-step optimization

algorithm that used a mixed-integer nonlinear programming (MINLP) stage-wise superstructure (SWS) approach for the initial network synthesis and a heuristic-based design approach for the individual exchangers. Then, Kazi et al.[7] presented an automated and fast approach based on the method of Short et al. The detailed exchanger models were obtained through the more rigorous models.

Metaheuristics are a good approach because they can deal with complex search spaces and solve models that include nonlinearities, nonconvexities, and discontinuities. In the HEN synthesis, the commonly used metaheuristic algorithms include simulated annealing (SA),[8−11] genetic algorithm (GA),[12−14] differential evolution (DE),[15] particle swarm optimization algorithm (PSO), and so forth.

PSO is a random optimization algorithm based on swarm intelligence that mimics the foraging behavior of birds. The basic idea of the PSO algorithm was first proposed by Kennedy and Eberhart in 1995.[16] Compared with other algorithms, the PSO algorithm requires fewer parameters to adjust. It has been successfully improved and applied to various problems recently.[17] The application of this algorithm in the synthesis
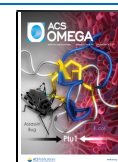
of HENs is relatively late. In 2008, Xia[18] optimized the integrated particle swarm algorithm by combining it with pinch point analysis for HENs with and without stream splits. Silva et al.[17] used the PSO algorithm to synthesize the HEN considering the stream splitting.

For HEN synthesis, the network structure, the split ratios of the stream (if considering the split flow), and the heat loads of heat exchangers must be optimized. The structure of the HEN needs to be described with integer variables. The split ratios and the heat loads are continuous variables. A one-level or two-level approach can be used during optimization. The one-level structure uses a single optimization algorithm or a hybrid optimization algorithm to optimize heat exchanger distribution and heat exchanger duty.[19−22] The two-level algorithm generally optimizes the position of the heat exchanger on the outer layer and the heat loads of the heat exchangers on the inner layer. The optimization of the inner and outer layers can use either the same or different optimization algorithms. Some of the studies on two-layer optimization have achieved good results, such as harmony search (HS)/sequential quadratic programming (SQP),[23] combined GA and PSO algorithm,[24] SA/SA approach,[25] SA/PSO,[9] SA/rocket fireworks optimization.[10] It should be pointed out that the two-level optimization algorithm is not necessarily better than one-level methods, as both methods have obtained satisfactory results.[26]

PSO has the advantages of good robustness and fast convergence on solving nonlinear, nondifferentiable, and multimode continuous optimization problems. However, it is more sensitive to parameters when dealing with high-dimensional or more complex optimization problems. Compared with GA, PSO is easier to fall into local optimum. Therefore, the PSO algorithm still has much space for improvements, such as population topology,[27,28] algorithm parameters,[29] particle velocity update strategy,[30−34] and hybrid PSO.[35,36]

The standard PSO algorithm updates the speed of the individual according to the individual and global historical optimal solutions, which can easily result in convergence to local optima. In response to this defect, different speed updates and improvement models have been proposed. Mendes et al.[30] presented a fully informed particle swarm optimizer algorithm by combining the historical optimal solutions of all particles in the neighborhood, which improved the accuracy of the algorithm. Liang et al.[31] proposed a comprehensive learning particle swarm optimizer (CLPSO) algorithm by employing all other particles' historical best information to reorganize learning items to update a particle's velocity. This algorithm greatly improves the performance of solving high-dimensional nonlinear and multimodal functions. Then, Liang,[32] Tang,[33] Nasir,[34] and others improved the PSO algorithm to increase its convergence speed. At present, the application of CLPSO in the HEN synthesis has not been reported.

The CLPSO algorithm promotes the full exchange of information among particles in the population and enhances the global exploration ability, but the local search ability decreases, and the convergence speed slows down. In order to converge to the optimal value, the number of evolutions is increased. In addition, the solution quality of CLPSO is largely determined by particles' best previous position (pbest), which is originally generated by HEN initialization. Thus, the solution may be unstable due to different initial pbest. In this paper, a new method of initializing HENs and renovating

the infeasible solution is proposed to improve the pbest quality and reduce the initial cost and the number of evolutions.

The remainder of this paper is organized as follows. In Section 2, the mathematical model of the HEN is given. In Section 3, the CLPSO algorithm is briefly introduced, the new initialization and renovation method is proposed, and the algorithm's implementation process is given. In Section 4, four large and medium-sized typical cases are simulated to verify the effectiveness of the proposed method. In Section 5, we present our conclusions.

2. MATHEMATICAL MODEL OF THE HEN WITHOUT STREAM SPLITS

The SWS developed by Yee and Grossmann is usually used to conduct HEN synthesis.[37−39] In this study, the modified SWS
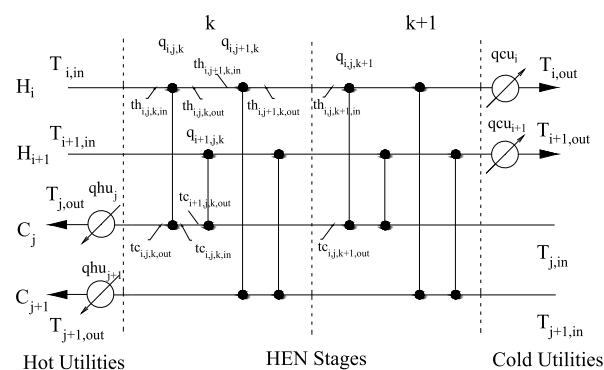

Figure 1. SWS of the HEN without stream splits.

model with no splits is adopted.[9,24,25] The simplification of no stream split can reduce the number of optimization variables and shorten the calculation time, especially for the large-scale network system. In addition, taking into account the additional piping, valves, and flow control system caused by stream splits, a slightly higher total annual cost (TAC) may also be acceptable.[9] Zhaoyi et al.[24] used a GA/PSO combination with modifications in the classic SWS formulation, in which splits were not considered or considered only in few stages. Peng and Cui[25] developed a two-level SA approach to handle the HEN synthesis problem considering the SWS with no split. Pavão et al.[9] presented a two-level no-split HEN synthesis hybrid method. SA was used for topology optimization, while continuous heat load variables were handled with PSO. The optimal results have a lower TAC when compared to other no-split HENs and even to some HENs with splits.

The HEN is composed of hot streams, cold streams, stages, and two utility sections. As shown in Figure 1, any two adjacent hot streams H_i and H_{i+1}, two adjacent cold streams C_j and C_{j+1}, two stages k and $k + 1$, as well as two utility sections are shown. The matches between cold and hot streams are carried out with the prescribed sequence. Cold and hot utilities are only used at both ends of the SWS model. The heat capacity flow rate and heat transfer coefficient of the stream are constant. The heat exchangers are all countercurrent.

2.1. Process Model. For the synthesis of HENs, it is necessary to determine the HEN structure and the duty of each heat exchanger, inlet and outlet temperature, and heat exchanger area. These parameters could be obtained through the process model.

2.1.1. Heat Loads. Heat exchanger heat loads

$$q_{i,j,k} = \text{wh}_i \cdot (\text{th}_{i,j,k,\text{in}} - \text{th}_{i,j,k,\text{out}}) \tag{1}$$

$q_{i,j,k}$ can also be calculated with cold streams

$$q_{i,j,k} = \text{wc}_j \cdot (\text{tc}_{i,j,k,\text{out}} - \text{tc}_{i,j,k,\text{in}}) \tag{2}$$

Heater heat loads

$$\text{qhu}_j = \text{wc}_j \cdot (T_{j,\text{out}} - \text{tc}_{1,j,\text{out}}) \tag{3}$$

Cooler heat loads

$$\text{qcu}_i = \text{wh}_i \cdot (\text{th}_{i,\text{NC,NS,out}} - T_{i,\text{out}}) \tag{4}$$

In the kth level, the inlet and outlet temperature of the same stream in adjacent heat exchangers satisfies the following relationship

$$\text{th}_{i,j+1,k,\text{in}} = \text{th}_{i,j,k,\text{out}} \tag{5}$$

$$\text{tc}_{i+1,j,k,\text{out}} = \text{tc}_{i,j,k,\text{in}} \tag{6}$$

When the heat exchange stream enters the $k + 1$st level from the kth level, the temperature

$$\text{th}_{i,j,k+1,\text{in}} = \text{th}_{i,\text{NC},k,\text{out}} \tag{7}$$

$$\text{th}_{i+1,j,k+1,\text{in}} = \text{th}_{i+1,\text{NC},k,\text{out}} \tag{8}$$

$$\text{tc}_{i,j,k+1,\text{out}} = \text{tc}_{\text{NH},j,k,\text{in}} \tag{9}$$

$$\text{tc}_{i,j+1,k+1,\text{out}} = \text{tc}_{\text{NH},j+1,k,in} \tag{10}$$

2.1.2. Heat Exchanger Area. Heat exchanger area

$$A_{i,j,k} = q_{i,j,k} / (U_{i,j} \cdot \Delta t_{i,j,k}) \tag{11}$$

$$U_{i,j} = \frac{\text{hh}_i \cdot \text{hc}_j}{\text{hh}_i + \text{hc}_j} \tag{12}$$

Heater area

$$A_{\text{hu},j} = \text{qhu}_j / (U_{\text{hu},j} \cdot \Delta t_{\text{hu},j}) \tag{13}$$

Cooler area

$$A_{\text{cu},i} = \text{qhu}_i / (U_{\text{cu},i} \cdot \Delta t_{\text{cu},i}) \tag{14}$$

In eq 11, U is the total heat transfer coefficient and Δt is the heat transfer temperature difference, which can be calculated by the Chen approximation method[40]

$$\Delta t_{i,j,k} = \left(dt_{ijk,1} \cdot dt_{ijk,2} \cdot \frac{dt_{ijk,1} + dt_{ijk,2}}{2} \right)^{1/3} \tag{15}$$

$$dt_{ijk,1} = \text{th}_{i,j,k,\text{in}} - \text{tc}_{i,j,k,\text{out}} \tag{16}$$

$$dt_{ijk,2} = \text{th}_{i,j,k,\text{out}} - \text{tc}_{i,j,k,\text{in}} \tag{17}$$

The cooler and heater's heat transfer temperature difference can also be calculated according to eqs 18–21.

$$\Delta t_{i,\text{CU}} = \left(dt_i \cdot (T_{i,\text{out}} - T_{\text{CU,in}}) \cdot \frac{dt_i + T_{i,\text{out}} - T_{\text{CU,in}}}{2} \right)^{1/3} \tag{18}$$

$$dt_i = \text{th}_{i,\text{NC,NS,out}} - T_{\text{CU,out}} \tag{19}$$

$$\Delta t_{j,\text{HU}} = \left(dt_j \cdot (T_{\text{HU,in}} - T_{j,\text{out}}) \cdot \frac{dt_j + T_{\text{HU,in}} - T_{j,\text{out}}}{2} \right)^{1/3} \tag{20}$$

$$dt_j = T_{\text{HU,out}} - \text{tc}_{1,j,\text{out}} \tag{21}$$

2.2. Constraints. *2.2.1. Constraints Corresponding to the Energy Balance.* The total heat load of each cold and hot stream and the heat load of each heat exchanger shall satisfy the following relationship

$$\text{wc}_j \cdot (T_{j,\text{out}} - T_{j,\text{in}}) = \sum_k \sum_j q_{i,j,k} + \text{qhu}_j \tag{22}$$

$$\text{wh}_i \cdot (T_{i,\text{in}} - T_{i,\text{out}}) = \sum_k \sum_i q_{i,j,k} + \text{qcu}_i \tag{23}$$

The minimum heat duty limit of a single heat exchanger

$$q_{i,j,k} \geq 0 \tag{24}$$

$$\text{qhu}_j \geq 0 \tag{25}$$

$$\text{qcu}_i \geq 0 \tag{26}$$

The maximum heat duty limit of a single heat exchanger

$$q_{i,j,k} \leq \min[\text{wc}_j \cdot (T_{j,\text{out}} - T_{j,\text{in}}), \text{wh}_i \cdot T_{i,\text{in}} - T_{i,\text{out}}] \tag{27}$$

$$\text{qhu}_j \leq \text{wc}_j \cdot (T_{j,\text{out}} - T_{j,\text{in}}) \tag{28}$$

$$\text{qcu}_i \leq \text{wh}_i \cdot (T_{i,\text{in}} - T_{i,\text{out}}) \tag{29}$$

2.2.2. Heat Transfer Temperature Difference Constraints. The heat transfer temperature difference should be a positive value. Meanwhile, to prevent the heat exchange area from being too large, it should be greater than a certain minimum value ε. However, in this model, the heat exchange area is a component of the total cost. The excessive heat exchange area will directly lead to the highest cost, and it should be eliminated. Therefore, to maintain the search range of the optimization process unaffected, the value of ε can be smaller (e.g., $\varepsilon = 0.1$).

$$dt_{ijk,2} \geq \varepsilon \tag{30}$$

$$dt_{ijk,1} \geq \varepsilon \tag{31}$$

2.3. Objective Function. In this paper, the minimum TAC is taken as the objective function, which includes the utility cost and the equipment cost. The utility cost is a simple function of utility loads of the network, while the equipment cost is usually composed of fixed cost and area cost. The total cost calculation formula is given as follows

$$\begin{aligned} \min : \text{TAC} = &\sum_i C_{\text{cu}} \cdot \text{qcu}_i + \sum_j C_{\text{hu}} \cdot \text{qhu}_j \\ &+ \sum_i \sum_j \sum_k (CF_{ij} \cdot z_{i,j,k} + CA_{ij} \cdot A_{i,j,k}{}^{B_{i,j}}) \\ &+ \sum_i (CF_{\text{cu}} \cdot z_{\text{cu},i} + CA_{\text{cu},i} \cdot A_{\text{cu},i}{}^{B_{\text{cu},i}}) \\ &+ \sum_j (CF_{\text{hu}} \cdot z_{\text{hu},j} + CA_{\text{hu}} \cdot A_{\text{hu},j}{}^{B_{\text{hu},j}}) \end{aligned} \tag{32}$$

where $z_{i,j,k}$, $z_{\text{cu},i}$, and $z_{\text{hu},j}$ is 1 or 0 based on whether their heat loads are greater than zero.
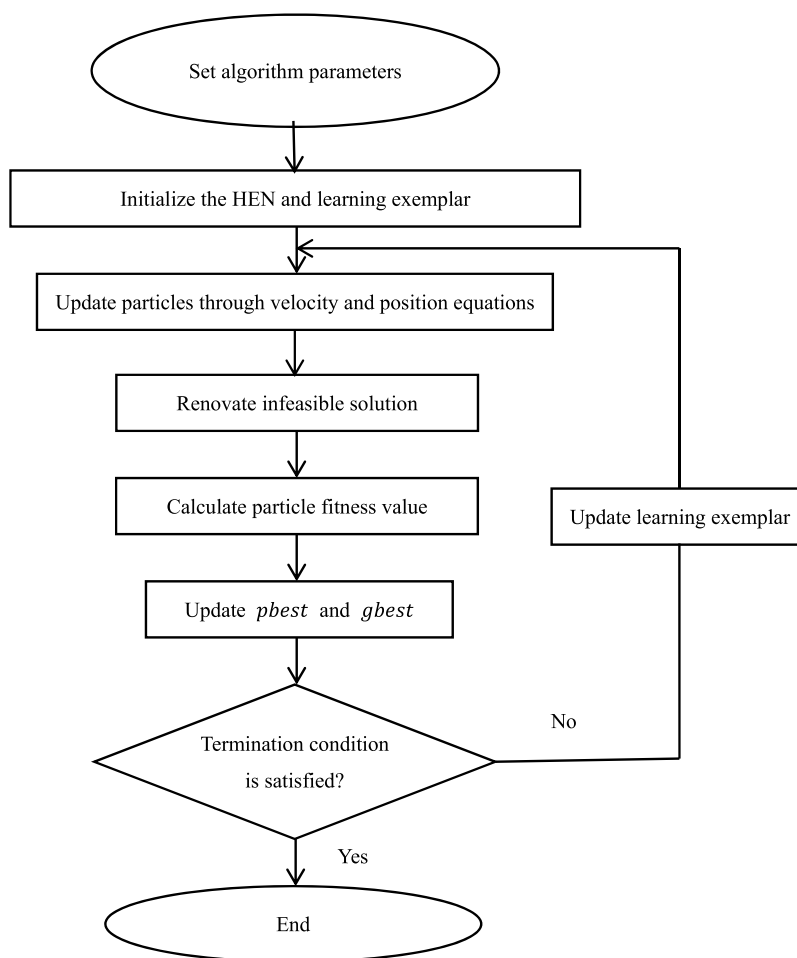
Figure 2. Algorithm procedure of HEN synthesis by CLPSO.

3. SOLUTION OF THE HEN MODEL

3.1. Comprehensive Learning Particle Swarm Optimizer. In the standard PSO, the particles update their velocity and position according to the following formula

Table 1. Streams and Cost Data for Case 1[a]

stream	T_{in}/°C	T_{out}/°C	FC_p/kW·°C^{-1}	h/kW·m^{-2}·°C^{-1}
H1	327	40	100	0.5
H2	220	160	160	0.4
H3	220	60	60	0.14
H4	160	45	400	0.3
C1	100	300	100	0.35
C2	35	164	70	0.7
C3	85	138	350	0.5
C4	60	170	60	0.14
C5	140	300	200	0.6
HU	330	250	100	0.5
CU	15	30	160	0.5

[a]Area cost = 2000 + 70A \$·year^{-1}, A in m^2. Hot utility (HU) cost = 60 \$·kW^{-1}·year^{-1}. Cold utility (CU) cost = 6 \$·kW^{-1}·year^{-1}.

$$v_{p,d}^{k+1} = \omega \cdot v_{p,d}^{k} + c_1 \cdot \text{rand} \cdot (\text{pbest}_{p,d}^{k} - x_{p,d}^{k})$$
$$+ c_2 \cdot \text{rand} \cdot (\text{gbest}_{d}^{k} - x_{p,d}^{k}) \tag{33}$$

Table 2. Comparison of Optimization Results of Case 1

source	method	TAC/\$·year^{-1}	units
Linnhoff and Ahmad[43]	Pinch technology	2.992×10^{6a}	13
Bergamini et al.[44]	outer approximation (OA)	2.935×10^{6}	15
Yerramsetty and Murty[45]	DE	2.942×10^{6}	15
Zhaoyi et al.[24]	GA/PSO	2.936×10^{6}	11
Zhaoyi et al.[24b]	GA/PSO	2.922×10^{6}	13
Peng and Cui[25]	SA/SA	2.935×10^{6}	15
Núñez-Serna and Zamora[46]	MSO	2.933×10^{6}	15
Pavão et al.[9]	SA/PSO	2.929×10^{6}	13
this work	CLPSO	2.928×10^{6}	13

[a]Revised by Fieg et al.[21] [b]HENs with splits.

$$x_{p,d}^{k+1} = x_{p,d}^{k} + v_{p,d}^{k+1} \tag{34}$$

where x_p and v_p are position and velocity vectors of the particle p, respectively, pbest$_p$ is the best previous position yielding the best fitness value for the particle p, and gbest is the best position discovered by the whole population. Each x_p represents a feasible solution to the optimization problem, and the optimization direction and distance of x_p are changed through the velocity of eqs 33 and 34.

In the PSO algorithm, the particles learn from pbest and gbest at the same time. If gbest falls into the local extreme value, all particles can be easily trapped in the local extreme
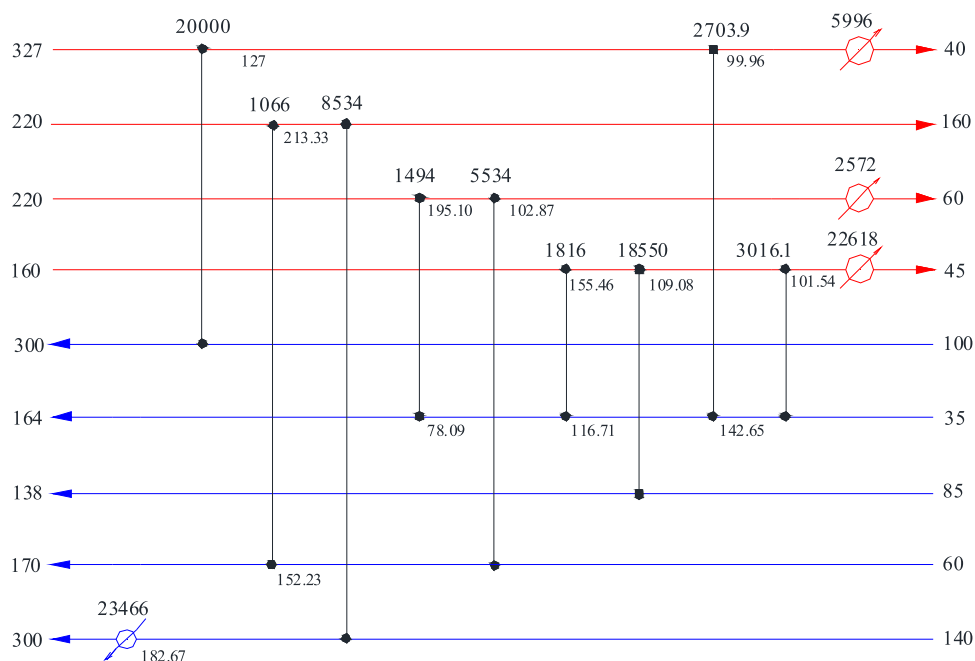
Figure 3. Optimal results for case 1.

Table 3. Streams and Cost Data for Case 2[a]

stream	T_{in}/°C	T_{out}/°C	FC_p/kW·°C−1	h/kW·m−2·°C−1
H1	180	75	30	2
H2	280	120	60	1
H3	180	75	30	2
H4	140	40	30	1
H5	220	120	50	1
H6	180	55	35	2
H7	200	60	30	0.4
H8	120	40	100	0.5
C1	40	230	20	1
C2	100	220	60	1
C3	40	190	35	2
C4	50	190	30	2
C5	50	250	60	2
C6	90	190	50	1
C7	160	250	60	3
HU	325	325	1	
CU	25	40	2	

[a]Area cost = 8000 + 500$A^{0.75}$ \$·year−1, A in m². HU cost = 80 \$·kW−1·year−1. CU cost = 10 \$·kW−1·year−1.

Table 4. Comparison of Optimization Results of Case 2

source	method	TAC/\$·year−1	units
Fieg et al.[21a]	hybrid GA	1.5109×10^6	15
Peng and Cui[25]	SA/SA	1.5272×10^6	19
Pavão et al.[9]	SA/PSO	1.5254×10^6	19
Chang et al.[4a]	MSTR	1.5010×10^6	15
this work	CLPSO	1.5254×10^6	19

[a]HENs with split.

value as well. In addition, each particle learns from all dimensions of its pbest, but they are not optimal in all dimensions. Based on this, the CLPSO algorithm removes the part of learning from gbest in the speed update formula and introduces a comprehensive learning strategy using all

Table 5. Streams and Cost Data for Case 3[a]

stream	T_{in}/°C	T_{out}/°C	FC_p/kW·°C−1	h/kW·m−2·°C−1
H1	385	159	131.51	1.238
H2	516	43	1198.96	0.546
H3	132	82	378.52	0.771
H4	91	60	589.545	0.859
H5	217	43	186.216	1
H6	649	43	116	1
C1	30	385	119.1	1.85
C2	99	471	191.05	1.129
C3	437	521	377.91	0.815
C4	78	418.6	160.43	1
C5	217	234	1297.7	0.443
C6	256	266	2753	2.085
C7	49	149	197.39	1
C8	59	163.4	123.156	1.063
C9	163	649	95.98	1.81
C10	219	221.3	1997.5	1.377
HU1	1800	800		1.2
HU2	509	509		1.0
CU	38	82		1.0

[a]Area cost = 26,600 + 4147.5$A^{0.6}$ \$·year−1, A in m². HU1 cost = 35 \$·kW−1·year−1, HU2 cost = 27 \$·kW−1·year−1, and CU cost = 2.1 \$·kW−1·year−1.

particles' pbest to construct a learning exemplar that can effectively promote the exchange of information between particles in different dimensions. The velocity update formula of particle p is given as follows

$$v_{p,d}^{k+1} = \omega \cdot v_{p,d}^k + c \cdot \text{rand} \cdot (\text{pbest}_{f_p,d}^k - x_{p,d}^k) \qquad (35)$$

where $f_p = [f_{p,1}, f_{p,2}, ...f_{p,D}]$ decides if the particle should follow its own or other's pbest on each dimension. The decision is made by learning the probability Pc_p. $\text{pbest}_{f_p,d}^k$ indicates the pbest of the particle p in the d dimension in the learning exemplar.
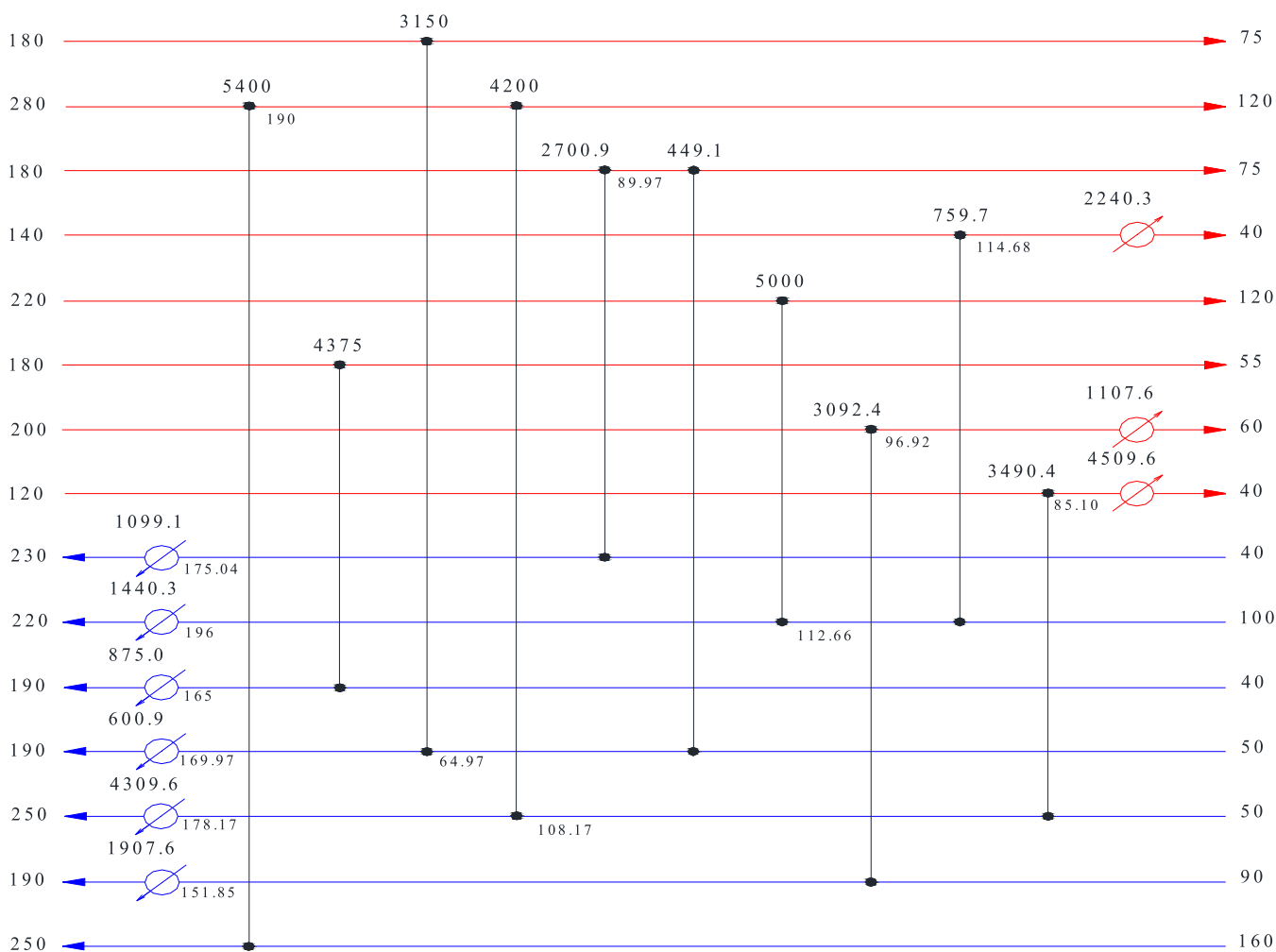
Figure 4. Optimal results for case 2.

Table 6. Comparison of Optimization Results of Case 3

source	method	TAC/$\cdot year^{-1}$	units
existing plant		8.856×10^6	18
Khorasany and Fesanghary[23a]	HS/SQP	7.436×10^6	18
Zhaoyi et al.[24]	GA/PSO	7.386×10^6	17
Zhaoyi et al.[24a]	GA/PSO	7.361×10^6	16
Pavão et al.[9]	SA/PSO	7.301×10^6	17
Chang et al.[4a]	MSTR	7.030×10^6	17
this work	CLPSO	7.276×10^6	19

[a]HENs with splits.

$$Pc_p = 0.05 + 0.45 \cdot \frac{\exp\left(\frac{10(p-1)}{ps-1}\right) - 1}{\exp(10) - 1} \quad (36)$$

where $p \in [1, ps]$ and ps is the population size.

The learning exemplar construction method of particle p is given as follows

(1) Particle p produces a random number between $[0,1]$ on $d = 1$ dimension and compares with Pc_p;

(2) If $rand \geq Pc_p$, learning from its own historical optimal value; otherwise, learning from other particles;

(3) When learning from the historical optimal value of other particles, the tournament selection procedure is adopted: arbitrarily select two particles whose speed has not been updated in the current dimension, and then, select the particle with the best fitness value as the learning object; and

(4) Repeat the abovementioned steps on other dimensions.

3.2. Algorithm Procedure. The procedures of using CLPSO to solve the HEN synthesis are shown in Figure 2. The detailed solution steps are illustrated, as follows:

(1) Set algorithm parameters.

Set the population size, the maximum number of iterations, the inertia weight ω, and the acceleration constant c_1. The population size and the maximum number of iterations depend on the complexity of the problem.

According to literature ([41]),

$$\omega = \omega_{min} + (\omega_{max} - \omega_{min}) \cdot \exp\left(-20 \cdot \left(\frac{CurCount}{LoopCount}\right)^6\right)$$

$$\omega_{max} = 0.9, \omega_{min} = 0.4 \quad (37)$$

According to literature ([32]), set $c_1 = 1.49445$.

(2) Initialize the HEN and learning exemplar.
(a) Initialize the structure of the HEN.

According to the superstructure of the nonsplit HEN, there are NH × NC × NS possible heat exchangers in the HEN except for the utility heat exchangers. With the increase in the
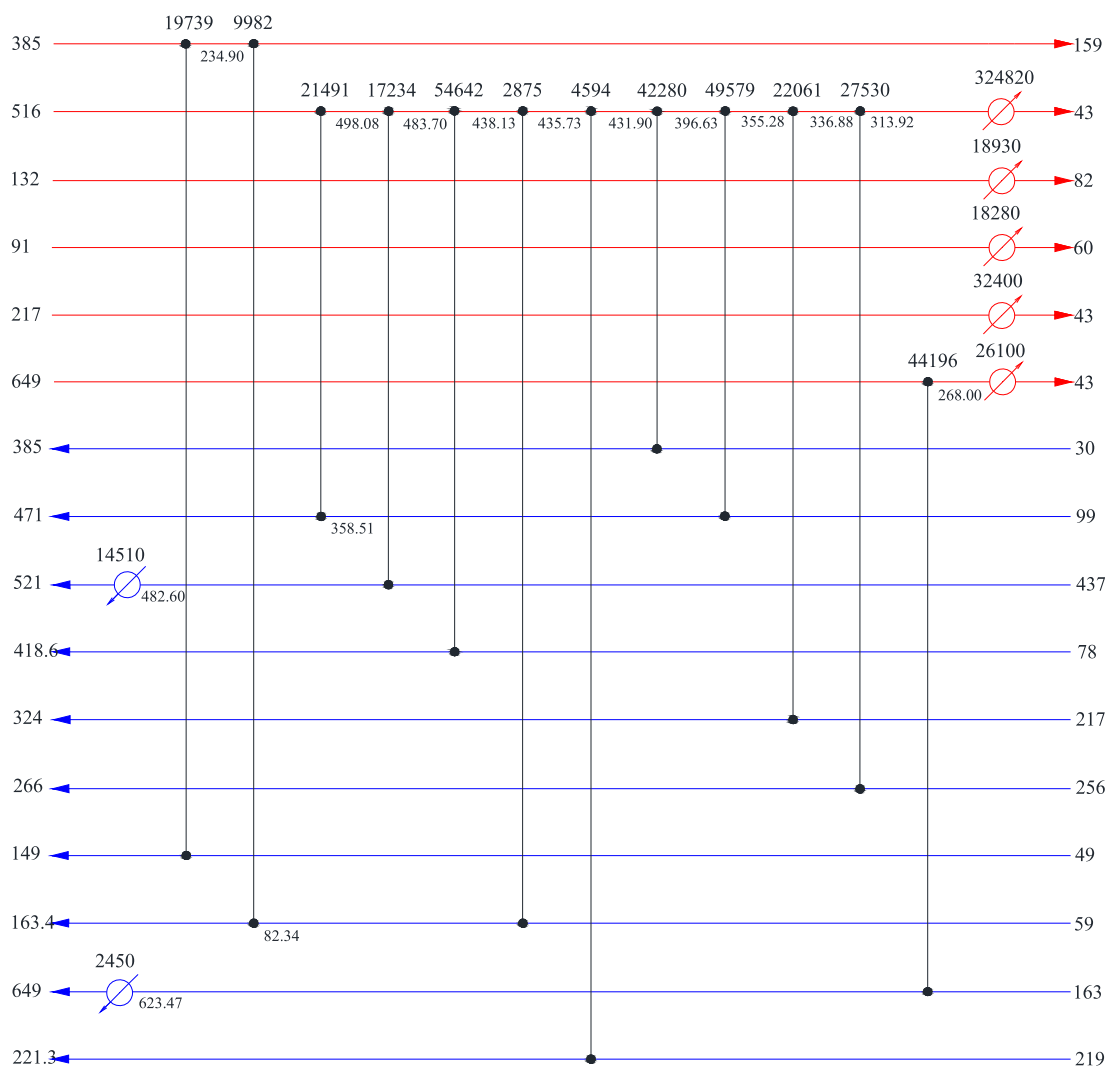
Figure 5. Optimal results for case 3.

number of streams, the number of heat exchangers increases sharply. However, Euler's general network theorem indicates that the minimum number of heat exchange equipment (including heat exchanger, heater, and cooler) required in the HEN is equivalent to the total number of streams.[42] Therefore, in order to improve the quality of the initial value, we stipulate that each stream can only exchange heat once in each stage when initializing the HEN structure. For the case where the number of cold and hot streams is not the same, streams with more numbers are taken as the mainstream, the corresponding stream is randomly selected for matching heat transfer, and the initial HEN structure $z_{i,j,k}$ is obtained. Such a network structure is close to the optimal structure. It can effectively reduce the initial cost of the HEN and maintain the diversity of the initial population.

(b) Initialize the heat duty of the HEN.

Under the premise of acceptable equipment investment, the more integrated the heat, the lower the total cost. When the heat load is initialized, it is generally assigned randomly from left to right in the order of heater, heat exchanger, and cooler. However, if the specified heaters' duty is too high, it will reduce the amount of heat integration and increase the utility consumption. Hence, in this paper, we start from the heat exchanger to initialize the heat loads. The maximum heat load

of each heat exchanger is calculated as the initial value of $q_{i,j,k}$ under the pregiven initial structure in step (a). The initial values of $q_{i,j,k}$ are assigned in the following four cases:

$$q_{i,j,k,\max} = \min(\mathrm{wh}_i \cdot (\mathrm{th}_{i,j,k,\mathrm{in}} - T_{i,\mathrm{out}}), \mathrm{wc}_j$$
$$(\mathrm{tc}_{i,j,k,\mathrm{out}} - T_{j,\mathrm{in}})) \tag{38}$$

$$q_{i,j,k,\max} = \min\left(\mathrm{wh}_i(\mathrm{th}_{i,j,k,\mathrm{in}} - T_{i,\mathrm{out}}), \mathrm{wc}_j(\mathrm{tc}_{i,j,k,\mathrm{out}} - T_{j,\mathrm{in}})\right.$$
$$\left., \frac{\mathrm{th}_{i,j,k,\mathrm{in}} - \mathrm{tc}_{i,j,k,\mathrm{out}} - \varepsilon}{1/\mathrm{wh}_i - 1/\mathrm{wc}_j}\right) \tag{39}$$

$$\mathrm{tc}_{i,j,k,\mathrm{out}} = T_{j,\mathrm{in}} + \mathrm{rand} \cdot (\min(\mathrm{th}_{i,j,k,\mathrm{in}}, \mathrm{tc}_{i,j,k,\mathrm{out}}) - \varepsilon$$
$$- T_{j,\mathrm{in}}) \tag{40}$$

$$q_{i,j,k,\max} = \min(\mathrm{wh}_i \cdot (\mathrm{th}_{i,j,k,\mathrm{in}} - T_{i,\mathrm{out}}), \mathrm{wc}_j$$
$$(\mathrm{tc}_{i,j,k,\mathrm{out}} - T_{j,\mathrm{in}})) \tag{41}$$

$$tc_{i,j,k,out} = T_{j,in} + rand \cdot (min(th_{i,j,k,in}, tc_{i,j,k,out}) - \varepsilon - T_{j,in}) \tag{42}$$

$$q_{i,j,k,max} = min\left(wh_i(th_{i,j,k,in} - T_{i,out}), wc_j(tc_{i,j,k,out} - T_{j,in}), \frac{th_{i,j,k,in} - tc_{i,j,k,out} - \varepsilon}{1/wh_i - 1/wc_j} \right) \tag{43}$$

$$q_{i,j,k} = q_{i,j,k,max} \cdot z_{i,j,k} \tag{44}$$

  i $th_{i,j,k,in} - tc_{i,j,k,out} \geq \varepsilon$ and $wh_i \geq wc_j$
  ii $th_{i,j,k,in} - tc_{i,j,k,out} \geq \varepsilon$ and $wh_i < wc_j$
  iii $th_{i,j,k,in} - tc_{i,j,k,out} < \varepsilon$ and $min(th_{i,j,k,in}, tc_{i,j,k,out}) - \varepsilon - T_{j,in} > 0$ and $wh_i \geq wc_j$
  iv $th_{i,j,k,in} - tc_{i,j,k,out} < \varepsilon$ and $min(th_{i,j,k,in}, tc_{i,j,k,out}) - \varepsilon - Tc_{j,in} > 0$ and $wh_i < wc_j$

Cooler heat duty

$$qcu_i = wh_i \cdot (th_{i,j,k,in} - T_{i,out}) \tag{45}$$

Heater heat duty

$$qhu_j = wc_j \cdot (T_{j,out} - T_{j,in}) - q_j \tag{46}$$

In eq 46, q_j is the total heat exchanged between cold stream j with all hot streams.

After the heat duty is initialized, $z_{i,j,k}$ is renewed depending on whether the exchangers' heat loads are zero.

(c) Initialize the learning exemplar.

Calculate the particle fitness value, initialize pbest and gbest, and initialize the learning sample by following the steps in Section 3.1.

(3) Update the particle velocity and position based on the eqs 34 and 35, respectively.
(4) Renovate the infeasible solution.

When updating the heat loads according to step (3), it is not restricted by the heat transfer temperature difference and energy conservation. This will result in many heat exchange processes that do not meet the heat transfer temperature difference, and the temperature of the flow after the heat exchange exceeds the target temperature. Therefore, it is necessary to adjust the infeasible solution to meet the requirements.

Common methods to deal with infeasible solutions include the penalty function method and renovation method. The penalty function method is used to add a penalty function when calculating the fitness of an infeasible solution in the random search process. Thereby, it can reduce the fitness of the individual and eliminate the infeasible solution in the optimization process. For the problem that the boundary of the feasible region and the infeasible region cannot be accurately determined, the selection of the appropriate penalty function and penalty factor is very difficult. The renovation method is used to find out the constraint conditions that are violated and transform the infeasible solution into a feasible solution. In this paper, the renovation method is used.

If the infeasible solution meets the four conditions in step (2), they can be adjusted based on the equation in step (2). Because all the infeasible solutions are caused by excessive heat loads, the maximum feasible heat loads after adjustment are

still taken as the heat duty of the heat exchangers. This can be consistent with the optimization direction. If the infeasible solution does not satisfy the above four conditions, then set $q_{i,j,k} = 0$.

According to the new $q_{i,j,k}$, recalculate the heat flow outlet temperature $th_{i,j,k,out}$ and the cold flow inlet temperature $tc_{i,j,k,in}$ and calculate heat loads of the cooler and heater. Also, update the HEN structure $z_{i,j,k}$.

$$th_{i,j,k,out} = th_{i,j,k,in} - q_{i,j,k}/wh_i \tag{47}$$

$$tc_{i,j,k,in} = tc_{i,j,k,out} - q_{i,j,k}/wc_j \tag{48}$$

(5) Update the learning exemplar.

Calculate the fitness value and update pbest and gbest. If particle p has not updated its pbest after continuous m generations of evolution, update the learning exemplar according to step 3.1. According to literature (32), set $m = 7$.

(6) When the termination condition is not met, return to step (4) for calculation, otherwise output the final result.

4. CASE STUDIES

In this section, four typical cases that are often studied in the nonsplit superstructure model are simulated. The results are

Table 7. Streams and Cost Data for Case 4[a]

stream	T_{in}/°C	T_{out}/°C	FC_p/kW·°C^{-1}	h/kW·m^{-2}·°C^{-1}
H1	180	75	30	2
H2	280	120	15	0.6
H3	180	75	30	0.3
H4	140	45	30	2
H5	220	120	25	0.08
H6	180	55	10	0.02
H7	170	45	30	2
H8	180	50	30	1.5
H9	280	90	15	1
H10	180	60	30	2
C1	40	230	20	1.5
C2	120	260	35	2
C3	40	190	35	1.5
C4	50	190	30	2
C5	50	250	20	2
C6	40	150	10	0.06
C7	40	150	20	0.4
C8	120	210	35	1.5
C9	40	130	35	1
C10	60	120	30	0.7
HU	325	325		1
CU	25	40		2

[a]Area cost = $8000 + 800A^{0.8}$ \$·year^{-1}, A in m^2. HU cost = 70 \$·kW^{-1}·year^{-1}. CU cost = 10 \$·kW^{-1}·year^{-1}.

compared with HENs with and without stream splits. The code was implemented and run in the MATLAB 2014a environment, and tests were performed in a 3.4 GHz Intel i7-6700 CPU and 16 GB of RAM.

4.1. Case Study 1. Case 1 includes four hot and five cold streams. The data for streams and heat exchanger and utility costs are shown in Table 1. Considering the tradeoff between energy and capital, Linnhoff and Ahmad[43] first adopted pinch technology to optimize this problem. In the following studies, most scholars adopt a two-level metaheuristic algorithm to
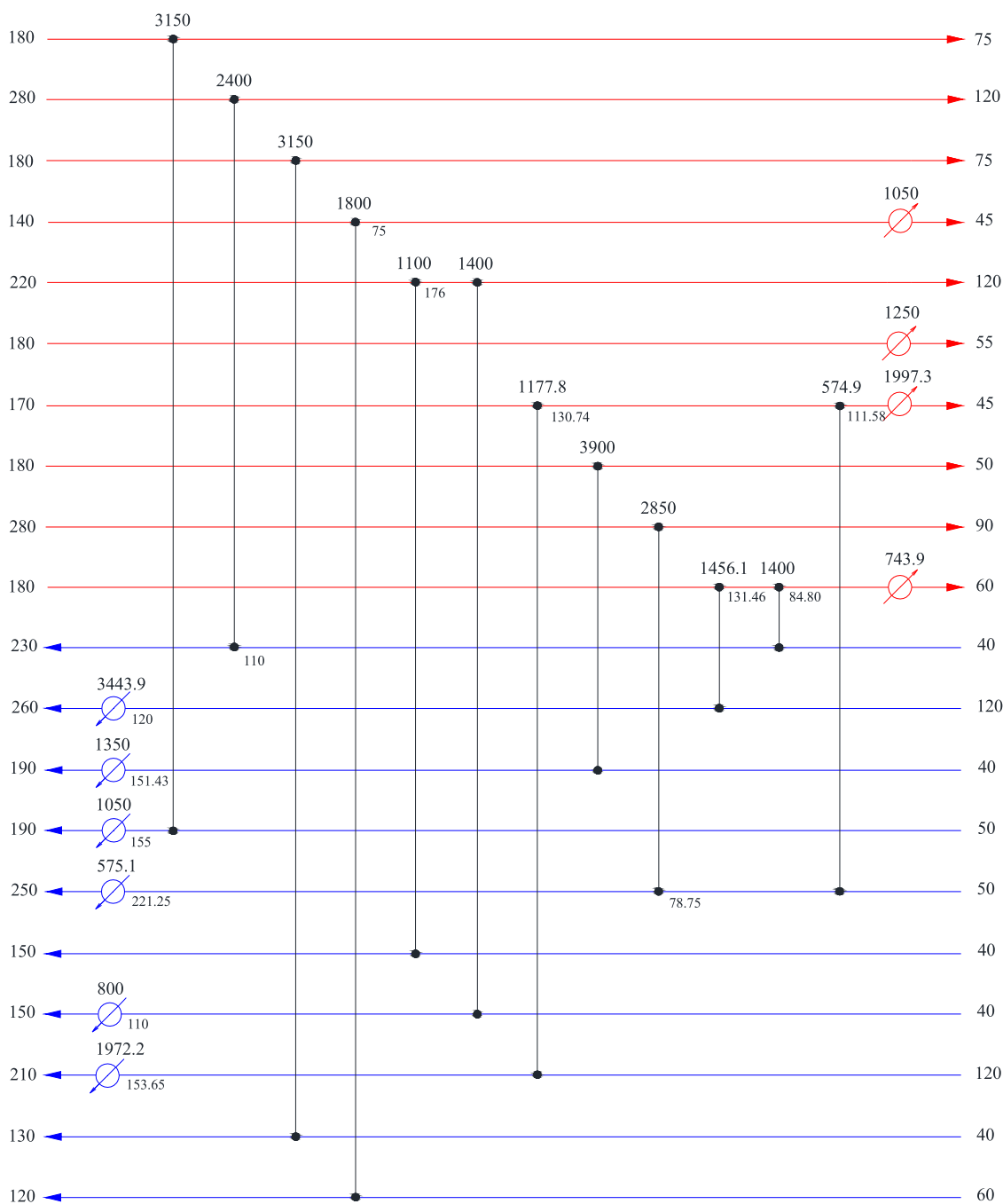
Figure 6. Optimal results for case 4.

Table 8. Comparison of Optimization Results of Case 4

source	method	TAC/$·year⁻¹	units
Luo et al.[22a]	hybrid GA	1.753×10^6	26
Pavão et al.[9]	SA/PSO	1.763×10^6	23
this work	CLPSO	1.739×10^6	22

[a]HENs with splits.

conduct the HEN synthesis (Table 2). In this paper, the single-level CLPSO algorithm is adopted. The number of particles is 300, and the maximum number of iterations is 5000. The optimal result is 2.928×10^6 $·year⁻¹ in about 641 s computation time. The result is slightly better than that

reported by Pavão et al.[9] and is close to the solution with splits reported by Zhaoyi et al.[24]

The optimal HEN structure and heat exchanger heat loads are shown in Figure 3, including 13 heat exchange units with the minimum heat transfer temperature difference of 15.35 °C. The numbers shown above the heat exchangers are heat loads, and the numbers below the streams are intermediate temperatures.

4.2. Case Study 2. Case 2 includes eight hot and seven cold streams. The stream and cost data are shown in Table 3. Note that Peng and Cui[25] used the two-level SA/SA algorithm to optimize the HEN structure and heat exchanger loads, and the optimal result was 1.5272×10^6 $·year⁻¹, but the calculation time was extremely long (2,316,647 s). It reflects

the limitation of the SA algorithm in dealing with large model problems. Pavão et al.[9] used the PSO algorithm in the inner level to optimize the HEN heat loads, with the calculation of 2456 s, and the TAC reduced to 1.5254×10^6 \$·year^{-1}. This is also the best result obtained so far by using the nonsplit superstructure in this case.

In this case, the number of particles is 300, and the maximum number of iterations is 15,000. After 4180 s calculation, the results are obtained that are similar to the work of Pavão (Table 4), and the minimum heat transfer temperature difference is 10.03 °C. The optimal HEN structure and heat exchangers' heat loads are shown in Figure 4. Compared with the results with splits obtained by Fieg[21] and Chang,[4] the difference is still obvious. It may be more appropriate to use the stream split model for this case.

4.3. Case Study 3. The data for case 3 are from the aromatics unit of a chemical plant, including 6 hot streams and 10 cold streams, two hot utilities with different temperature levels, and a cold utility. The problem data are shown in Table 5, which uses the number of particles of 300 and the maximum number of iterations of 15,000. The solution was achieved in 5098 s and is shown in Figure 5, including 19 heat exchange units. The minimum heat transfer temperature difference is 28.21 °C. The comparison of results is shown in Table 6.

The optimal result is 7.276×10^6 \$·year^{-1}, which is a significant improvement over the reported no-split results. However, compared with the optimal result considering stream splits reported by Chang et al.,[4] the TAC is still much higher.

4.4. Case Study 4. Case 4 consists of 10 hot and 10 cold streams and one hot and one cold utility. The input data for this problem are given in Table 7. Taking the number of particles as 300, the maximum number of iterations is 15,000. The best network was obtained with a computation time of 6092 s, which is shown in Figure 6. The TAC for this configuration is 1.739×10^6 \$·year^{-1}. The solution is compared and shown in Table 8. This solution is better compared to a split result and a nonsplit result. There are 22 heat exchange units, and the minimum heat transfer temperature difference is 13.35 °C.

5. CONCLUSIONS

In this paper, the CLPSO algorithm is used to optimize the HEN synthesis based on the nonsplit multistage superstructure model. CLPSO introduces a comprehensive learning strategy to construct samples using all the particles' own optimal values. It can effectively promote the full exchange of information among particles in the population and enhance the global exploration ability. To improve the stability and convergence speed of the algorithm, the study develops a new initialization and infeasible solution renovation method. When initializing the HEN structure, each stream is allowed to exchange heat randomly only once in each stage. After the initial HEN structure is obtained, the heat loads of the heat exchangers are first initialized. This can greatly reduce the number of initial heat exchangers and increase heat integration. In correcting the infeasible solution, a method similar to that of initializing the heat loads is adopted to retain the optimal results to the maximum extent possible.

Four typical cases are investigated, and the results are compared with the nonsplit and split solutions. Lower or equal TAC HENs can be obtained in a reasonable computation time when compared to no-split HENs and some split HENs. However, the setting of nonsplit also limits the possibility for

some cases to find better solutions, resulting in a relatively large gap compared with the optimal split results. The method used in this paper has a simple model and high solving efficiency. But in the later stage of calculation, the local search capability needs to be strengthened. In the following research, we will try to solve this problem and apply it to deal with more complex HEN synthesis.

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https://pubs.acs.org/10.1021/acsomega.1c03424

Notes

The authors declare no competing financial interest.

■ NOMENCLATURE

Superscript

B exponent for area cost
k number of iterations

Subscript

cu cold utilities
d dimension of particle
f particles' index the particle p should follow
hu hot utilities
i index of hot streams
in inlet temperatures of exchangers
j index of cold streams
k index of stages
max maximum value
min minimum value
out p outlet temperatures of exchanger index of particles

Variables

A area of exchangers, m^2

C	specific hot and cold utility cost per unit duty, $\$\cdot kW^{-1}\cdot year^{-1}$
c	acceleration constant
CA	area cost coefficient
CF	fixed charge, $\$\cdot year^{-1}$
CurCount	current number of iterations
dt	temperature difference at the hot or cold end of the heat exchanger, °C
hc	heat transfer coefficient for cold streams, $kW\cdot m^{-2}\cdot °C^{-1}$
hh	heat transfer coefficient for hot streams, $kW\cdot m^{-2}\cdot °C^{-1}$
i	index of particle
gbest	the best position of the whole population
LoopCount	total iteration number
m	the set number of no evolutions
NC	number of cold streams
NH	number of hot streams
NS	number of stages
pbest	the best previous position for particle i,
Pc	learning probability
ps	population size
q	heat load in a heat exchanger, kW
qcu	heat load in a cooler, kW
qhu	heat load in a heater, kW
rand	uniform random number in $[0,1]$
T	target temperature, °C
Δt	logarithmic mean temperature difference (LMTD), °C
TAC	total annual cost, $\$\cdot year^{-1}$
tc	cold stream temperature, °C
th	hot stream temperature, °C
U	the overall heat transfer coefficient, $kW\cdot m^{-2}\cdot °C^{-1}$
v	particle velocity
wc	cold stream heat capacity, $kW\cdot °C^{-1}$
wh	hot stream heat capacity, $kW\cdot °C^{-1}$
x	particle position
z	binary variables representing the existence of heat exchangers

Special characters

ε	minimum temperature difference at the hot or cold end of the heat exchanger
ω	inertia constant

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