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Application of a genetic algorithm to optimize the refrigerant circuit of fin-and-tube heat exchangers for maximum heat transfer or shortest tube

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Abstract

Optimization of the refrigerant circuit (RC) of a fin-and-tube heat exchanger can increase its heat exchange capacity or decrease its cost. The genetic algorithm is one of the suitable optimization methods, however it needs to be improved for RC optimization of fin-and-tube heat exchangers. An improved genetic algorithm (IGA) is proposed for RC optimization. In the IGA, the RC solutions are represented by one-dimensional integer strings which can save both computer memory and decoding time. RC correction operators are developed and embedded in the entire genetic process with the goal of avoiding physically impossible solutions. The knowledge-based RC generation method, greedy RC crossover method, greedy RC mutation method and all-previous-population based selection method are developed in order to improve the efficiency of the genetic evolution process for RC optimization. Case studies with 3 different heat exchangers show that both the optimization speed and the quality of the output optimal solution of IGA are better than those of the conventional genetic algorithm. A 0–40% decrease in total length of joint tubes is obtained after optimization with the IGA with the target of obtaining the shortest joint tubes. In addition, a 2.8–7.4% increase in heat exchange capacity is obtained after IGA optimization with the target of maximum heat transfer.

Keywords: Fin-and-tube; Heat exchanger; Refrigerant circuit; Optimization; Genetic algorithm

1. Introduction

Fin-and-tube heat exchangers are widely applied as evaporators and condensers in refrigeration systems. Cost reduction and capacity maximization are the two major targets of optimization for such heat exchangers. Shortest tubes are expected in practical design of the heat exchangers in order to reduce the cost. Changing RC (Refrigerant Circuit) for heat exchanger optimization is more convenient and is cost saving compared with other optimization methods of changing the overall dimensions or fin and tube geometries [1,2], because the latter optimization methods [1,2] are confined by many factors, such as installation space, manufacture facilities, etc. It has been proved that RC has significant effect on heat exchanger performance [3–5], and the optimal RC for one refrigerant is different from that for another refrigerant [4,7,8]. Wang et al. [3] experimentally studied eight air-cooled condensers including six 1-circuit and two 2-circuit arrangements, and found that counter-cross flow gave better performance than other arrangements. Liang et al. [5] analyzed six refrigerant circuits by using their verified model, and found that suitable refrigerant circuit arrangements might reduce the heat transfer area by around 5% in coil design. Only limited number of RCs can be investigated by manual experimental analysis method [3,4] or manual numerical analysis method [5,6], and the optimization results from such methods may also be limited. RC optimization programs can help finding the optimal RC solutions as well as reducing the development time and cost since it uses computer to do the optimization automatically.

Suitable optimization methods for RC optimization need to be developed considering the complexity of the RC optimization. Many factors should be considered simultaneously to design an optimal RC, such as the number and positions of the inlets and outlets, the number and positions of the inner con-

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Nomenclature

A_o	total airside surface area	m^2
A_i	tube inside surface area	m^2
C_1, C_2	constant numbers	
$F(j)$	fitness value of No. j individual	
G	mass flux	$kg\ m^{-2}\ s^{-1}$
h	specific enthalpy	$kJ\ kg^{-1}$
L	total length of joint tubes	m
L_b	length of single joint tube on the backside of the heat exchanger	m
L_{adj}	maximum length of single joint tube between two adjacent tubes of same row or adjacent rows	m
L_r	reference total length of joint tubes	m
L_{x-y}	joint tube length between tubes #x and #y	m
m	inlet path number or outlet path number	
M	mass flow rate	$kg\ s^{-1}$
N	total tube number in the heat exchanger	
OA	offspring individual A	
p	pressure	kPa
PA	parent individual A	
PB	parent individual B	
Q	heat exchange capacity	W
Q_0	minimum heat exchange capacity	W
T	temperature	K
X	the variable or integer string for representing RC	
$X[i]$	the ith element in X	

Greek symbols

α	heat transfer coefficient	$kW\ m^{-2}\ K^{-1}$
δ	weight factor	
Δp	pressure drop	Pa
η_0	fin surface efficiency	

Subscripts

a	air
acc	acceleration
f	friction
in	inlet
out	outlet
r	refrigerant
wall	tube wall

Abbreviations

APPSM	all-previous-population based selection method
CPSM	current-population-based selection method
GA	genetic algorithm
IGA	improved genetic algorithm
RC	refrigerant circuit
SGA	standard genetic algorithm
***	undetermined part in X

fluent/divergent points, etc. It is difficult to deduce rules, such as the gradient equations, to directly guide the optimization process. Moreover, there are numerous RC candidates for a given heat exchanger, and the exhaustive searching algorithm is incompetent for searching the whole solution space. Taking a 24-tube heat exchanger as an example, there are about 3×10^{23} possible solutions. The exhaustive searching method may cost at least 4.2×10^4 years even a 100 GHz CPU computer is applied. Therefore, suitable RC optimization method is needed.

Domanski, Kaufman, et al. [9,10] used domain knowledge-based structure modifying operators and symbolic learning method to optimize RC of a fin-and-tube evaporator, and reported that the RC optimization program had the capability to generate designs with capacity equal or superior to that of best human designs. However the process of generating the rules for symbolic learning in that method is quite complicated and the generated rules may confine the diversity of the solutions because some tube connections are fixed during the optimization process. Therefore, simpler optimization methods for RC optimization of fin-and-tube heat exchangers are expected.

Genetic Algorithm (GA) is relatively easy to operate [11], can find the global optimal solution [12] and provide good results for some combinatorial optimization problems [13–16]. But it cannot be directly applied for RC optimization due to the complicated nature of RC optimization. In order be used in RC optimization of fin-and-tube heat exchangers, traditional GA need to be improved by overcoming the following 4 problems: (1) How to represent the RCs. The RC representation method should not only be easy for computer to distinguish different RCs and perform genetic operations, but also be space saving and easily decoded. (2) How to automatically generate the feasible RCs. Not only feasible initial RCs but also new feasible RCs in the optimization process should be automatically generated. (3) How to avoid the infeasible solutions generated by the genetic operators. Infeasible solutions are easily produced with the traditional genetic operators [9], and measures should be taken to avoid the infeasible solutions. (4) How to develop efficient genetic operators to improve the optimization speed. Optimization process that takes too much time is unbearable for practical applications, and more efficient genetic operators must be developed.

In this paper, the method of solving the above 4 problems are presented, and an improved genetic algorithm (IGA) for RC optimization of heat exchangers is introduced. Case studies and conclusions are offered in the last part of the paper.

2. Description of the RC optimization targets and constraints

Two targets of the refrigerant circuit optimization are considered, one is to obtain the shortest tubes, and the other is to obtain the maximum heat exchange capacity of the heat exchanger. Tubes in a heat exchanger include the finned tubes in the main body of the heat exchanger and the joint tubes. As the length of the entire finned tubes is not changeable when the overall dimension of the heat exchanger is fixed, the objective of getting the shortest tubes is equivalent to obtaining the shortest joint tubes. All the working conditions and the structural parameters except the refrigerant circuit are fixed during the optimization. Other parameters of the optimization problems are listed below:

(1) To obtain the shortest joint tubes:

min $L(X)$, X is the variable of refrigerant circuit that needs to be optimized

s.t. $Q \geqslant Q_0$; $L_b \leqslant L_{adj}$; $m_{in} = C_1$; $m_{out} = C_2$

where Q and Q_0 are the heat exchange capacity related to the X and the minimum value of the heat exchange capacities of all feasible RC solutions, respectively; L_b and L_{adj} are the length of single joint tube on the backside of the heat exchanger and the maximum length of single joint tube between two adjacent tubes of same row or adjacent rows, respectively; m_{in} and m_{out} are the numbers of the inlet paths and the outlet paths, respectively; C_1 and C_2 are two constant numbers.

(2) To obtain the maximum heat transfer:

max $Q(X)$, X is the variable of refrigerant circuits that needs to be optimized

s.t. $L_b \leqslant L_{adj}$; $m_{in} = C_1$; $m_{out} = C_2$

Refrigerant circuit controls the refrigerant distribution in the paths. Unsuitable refrigerant distribution in evaporators may result in dry-out of circuits and finally result in poor heat transfer and waste of the heat transfer area, while unsuitable refrigerant distribution in condensers may create zones of reduced heat transfer due to high liquid loading. Moreover, unsuitable refrigerant distribution may lead to high temperature difference between adjacent tubes, which causes the reversed heat conduction through the fins and degrades the performance of the heat exchangers [3,17]. Changing the refrigerant circuit can help to adjust the refrigerant distribution in the heat exchangers and to obtain a suitable refrigerant distribution in a heat exchanger. Therefore the maximum heat transfer can be expected for some optimal RCs. On the other hand, the total length of joint tubes may also be reduced if the minimum heat exchange capacity of the heat exchanger is fixed.

3. Improved Genetic Algorithms (IGA) for RC optimization

The standard GA (SGA) uses a population of individuals to perform the optimization. It contains 6 steps of coding/decoding, population initialization, evaluation, selection (or reproduction), crossover and mutation. The individuals are represented with strings in a binary or decimal format, and the initial individuals are randomly generated from the search space. Each individual is evaluated and assigned with a ‘fitness’ value determined by the fitness function. The higher ‘fitness’ value an individual has, the higher chance it would survive to the next generation during the selection process. Some individuals in the new generation are generated from individuals selected at a given probability by using crossover and mutation operations. Crossover operation generates new individuals by exchanging the data between two randomly chosen individuals, and mutation operation generates new individuals by randomly changing data of one randomly chosen individual. The individuals in the new generation are evaluated and the process is repeated until the given maximum number of generations is reached or convergence is reached.

When applying the GA into the domain of heat exchanger refrigerant circuit optimization, not only the methods of above 6 operations should be improved, but also additional correction operators should be developed in order to avoid the shrinking of the searching space by completely abandoning all infeasible solutions.

3.1. RC representation method

A suitable RC representation method should be able to describe most types of fin-and-tube heat exchangers. As heat exchangers with both inner divergences and inner confluences are rarely used in air conditioners, only the following three types of heat exchangers are needed to describe: (1) with inner divergences; (2) with inner confluence; (3) neither with inner divergences nor with inner confluences. Figs. 1(a) and (b) show the schematic of the RCs for i-column and j-row heat exchangers with inner divergence and inner confluence, respectively. In Fig. 1, the solid lines represent the return bends on the near side of the heat exchanger, and the broken lines are the return bends on the far side. The arrows on the solid lines reflect the direction of the refrigerant flow in the bends. In order to identify each tube in the heat exchanger, the tubes are numbered from 1 to N from front row to back row and from bottom to top of the heat exchanger, and the inlet collecting tube and outlet collecting tube are numbered as 0 and $N+1$ respectively.

The RC representation method applied in GA should also satisfy the following 2 requirements: (a) the representation codes for RC can be easily decoded to the form used by the RC evaluation software and can be easily manipulated by the genetic operators; (b) The RC representation codes can save both computer memory and decoding time because large number of RC solutions are manipulated simultaneously in GA.

A method with two-dimensional adjacent matrix to describe the RC of a fin-and-tube heat exchanger is developed for steady-state simulation, in which only single RC needs to be described and only single two-dimensional adjacent matrix needs to be stored [6]. But the number of the RCs stored in the optimization process is very large and it may cost too much storing space and decoding time if the two-dimensional adjacent matrix is used to describe the RC. Take one RC containing N tubes as an example, the adjacent matrix is an integer matrix of at least $(N+2)\times(N+2)$ elements and needs at least $(N+2)\times(N+2)$ times of searching operation in order to trace the refrigerant flow according to the adjacent matrix. The storing space and decoding time may increase rapidly when the number of RC increases. Furthermore, it is difficult to manipulate the adjacent matrix by using genetic operators because little modification of the adjacent matrix may lead to infeasible tube connections in the RC. Thus, the adjacent matrix is not suitable for represent-

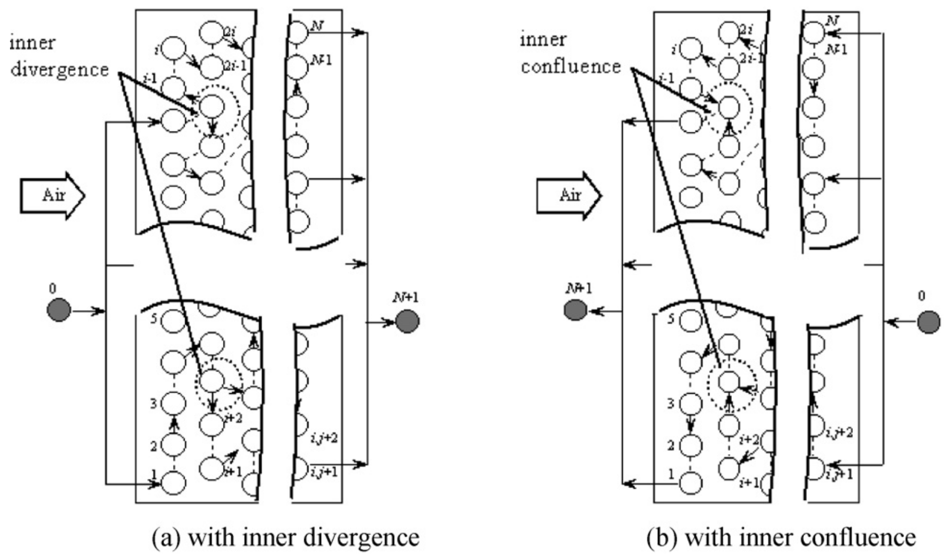


Fig. 1. Schematic of the RCs for i-column and j-row heat exchanger.

ing the RC in the GA, and a new RC representation method should be developed.

In this paper, a one-dimensional integer string is developed, as shown below, to represent the RC:

$$X = \{x_1, x_2, \ldots, x_m, x_{m+1}, x_{m+2}, \ldots, x_{m+N}\} \tag{1}$$

where m is the inlet path number for heat exchangers without inner divergences, or the outlet path for the heat exchanger with inner divergences; $x_1, x_2, \ldots, x_{m+N}$ are the array of the tube no. For heat exchangers without inner divergence, the first m integers of "$x_1, x_2, \ldots, x_m$" denote the no. of inlet tubes, and the next N integers "$x_{m+1}, x_{m+2}, \ldots, x_{m+N}$" denote the no. of the tubes connecting to the end of tube #1, tube #2, …, tube #N, respectively. For the heat exchanger with inner divergences, the first m integers of "$x_1, x_2, \ldots, x_m$" denote the no. of outlet tubes, the next N integers "$x_{m+1}, x_{m+2}, \ldots, x_{m+N}$" denote the no. of the tubes connecting to the head of tube #1, tube #2, …, tube # N, respectively. Take the RC shown in Fig. 1(a) as an example, $x_1 = ij + 1, \ldots, x_m = N, x_{m+1} = N + 1, x_{m+2} = 1, x_{m+3} = 2, \ldots, x_{m+i} = i - 1, \ldots, x_{m+N-1} = N - 2, x_{m+N} = N - 1$. Thus a string can uniquely represent a RC of a heat exchanger with or without inner divergences.

The above RC representation method with one-dimensional integer string has 2 advantages. The first advantage is that the refrigerant-flow-trace can be simply and clearly described. For the heat exchangers without inner divergences, the tube connection of the RC can be obtained from X as: $\#0 \to \#x_1, \#0 \to \#x_2, \ldots, \#0 \to \#x_m, \#1 \to \#x_{m+1}, \#2 \to \#x_{m+2}, \ldots, \#N \to \#x_{m+N}$. For the heat exchangers with inner divergences, the tube connection of the RC can be obtained from X as: $\# x_1 \to \#(N+1), \#x_2 \to \#(N+1), \ldots, \#x_m \to \#(N+1), \#x_{m+1} \to \#1, \#x_{m+2} \to \#2, \ldots, \#x_{m+N} \to \#N$. When $x_{m+i} = x_{m+j}$ ($i, j = 1, 2, \ldots, N$ and $i \neq j$), the tube $\#x_{m+i}$ is the confluence tube of tube #i and tube #j for the heat exchanger without inner divergences, or is the divergence tube of tube #i and tube #j for the heat exchanger with inner divergences. The second advantage is that it can save both computer memory and decoding time. The integer string only needs $(N + m)$ integer memory space to describe the RCs of a heat exchanger with N tubes, which can save much computer memory comparing with the $(N + 2) \times (N + 2)$ integer memory space used in the two-dimensional adjacent matrix [6]. It only needs $(N + m)$ times of searches for decoding the string, which is faster than the two-dimensional adjacent matrix [6] using $(N + 2) \times (N + 2)$ times.

3.2. RC generation method

RC solutions should be automatically generated in GA especially during the population initialization stage, and the existing method of randomly generating RC solutions cannot meet the requirement, therefore a new method must be developed. Randomly generating RC solutions can be used to generate the RC with only one inlet and one outlet, but it cannot be used to generate the RC with multiple inlets and outlets because infeasible solutions may easily be generated. The reason of easily generating infeasible solutions for the RC with multiple inlets and outlets is that the specific tube connection constraints for the different kinds of tubes are not complied during the random RC generation process. The tubes in RC with multiple inlets and outlets can be generally divided into 4 kinds of common tubes, inlet tubes, outlet tubes, and inner confluence or divergence tubes. The tube connections in the practical RC must comply with the following constraints: (1) A common tube should have only one inlet and one outlet; (2) An inlet tube must begin with tube #0 and end with one common tube; (3) All the refrigerant must confluent to same end of the confluence tube, or diverge from same end of the divergence tube; (4) One tube should not appear in one path more than one time to avoid the refrigerant flow loop in the RC. Infeasible solutions may occur if the above constraints are not correctly considered during the RC generation process. Therefore, the computer should be guided to consider these constraints in order to automatically generate feasible solutions.

A novel RC generation method is developed to guide the computer to distinguish different kinds of tubes and to search the valid adjacent tubes for them. The novel method randomly determines the inlet tubes, outlet tubes and confluence/divergence tubes in sequences at first, then randomly selects the valid foreside tube for those without foreside tube until all the tubes are included in the RC. As the inlet tubes, outlet tubes, confluence/divergence tubes and the adjacent tubes have already been correctly determined, the possibility of infeasible solutions is greatly reduced. The random operation in each step can guarantee the diversity of the generated RCs.

The method for generating the RC without inner divergences is shown in the following steps 1–4. The undetermined parts in X are abbreviated as *** in order to clearly show the variation of X during the RC generation process:

(1) Randomly determine the inlet tubes: $X = \{x_1, x_2, \ldots, x_m, ***\}$.
(2) Randomly determine the outlet tubes: $X = \{x_1, x_2, \ldots, x_m, ***, N+1, ***, N+1, ***\}$.
(3) Randomly determine the confluence tubes: $X = \{x_1, x_2, \ldots, x_m, ***, N+1, ***, x_{m+i}, ***, N+1, ***, x_{m+j}, ***\}$ ($x_{m+i} = x_{m+j}, i, j = 1, 2, \ldots, N$ and $i \neq j$. So the tube #i and tube #j converge to tube # x_{m+i}).
(4) Select the valid foreside tube for those tubes without foreside tube:

$$X = \{x_1, x_2, \ldots, x_m, x_{m+1}, \ldots, N+1, \ldots, x_{m+i}, \ldots, N+1, \ldots, x_{m+j}, \ldots, x_{m+N}\}$$

The method for generating the RC with inner divergences can be obtained by replacing "$N+1$" with "0", replacing "foreside" with "rear-side", and replacing "confluence" with "divergence" in the method for generating the RC without inner divergences. Step 3 can be skipped if the number of the inner confluence/divergence is set as 0.

Neighbor-tube-database for each tube is created at the beginning of the optimization process to generate better solutions. For the convenience of manufacture and for the target of obtaining the shortest joint tubes, each tube should be connected with its nearest neighbor tube. Creating neighbor-tube-database for each tube at the beginning of the optimization process can help to limit the length of the joint tubes. The adjacent tubes of each tube have priority to be selected during the process of randomly selecting foreside tube for those tubes without foreside tube.

3.3. *Method to avoid the infeasible solutions generated in the genetic optimization process*

Infeasible solutions may be produced in the genetic optimization process. The existing penalty method [18] does not avoid all the infeasible solutions, so such method is not suitable for treating with the infeasible solutions in RC genetic optimization process because one infeasible solution is enough to break the optimization program. However, the optimal solutions may be lost if we completely reject all the infeasible solutions because infeasible solutions may still contain better genes. Therefore, a better solution to avoid the infeasible solutions in GA is to modify and correct the infeasible solutions.

In this paper, five correction operators are developed to check and correct the infeasible solutions: (1) Judge and correct the sub-loop. The sub-loop is broken in suitable position and added to the shortest path. (2) Judge and correct the number of inlets and outlets. Rest numbers of tubes are randomly set as the inlet/outlet tube if the number of the inlets/outlets is less than the expected value, and rest numbers of inlet/outlet tubes are randomly inserted to the end of the shortest path if the number of the inlets/outlets is larger than the expected value. (3) Judge and correct the positions of the inlet tubes and outlet tubes. The positions of the inlet tubes and outlet tubes should not be in the middle of one path, and the path is broken before the position of inlet/outlet tube if it contains inlet/outlet tubes. (4) Judge and correct the refrigerant flow direction at divergence/confluence points. The divergence/confluence position on one path is moved even number of tube positions forward or backward to avoid this problem. (5) Judge and correct connection of the return bends according to the constraints. The RC is modified to satisfy the constraints for tube connections.

The traditional genetic operators can be used for RC optimization after applying the developed RC correction operators for avoiding the infeasible solutions. But effective genetic operators for RC optimization are still needed in order to obtain efficient RC optimization method due to the low efficiency of the traditional genetic operators for RC optimization.

3.4. *Effective genetic operators for RC optimization*

The traditional genetic method uses pure random genetic operations. With the pure random genetic operators, the worse solutions and better solutions have the same probability to be generated, the worse solutions may pullback the optimization progress, and so the optimization speed is slow. In order to speed up the optimization process, more effective crossover method, mutation method and selection method are needed.

3.5. *Greedy crossover*

The optimization speed may increase if better solutions are always generated during the crossover process. The greedy crossover method [19] can always generate better offspring solutions by greedily inheriting the better genes from the two selected parent individuals, but some tailor-made improvements are needed for generating feasible RC offspring solutions. The tube connections in RC have strict constraints, and must be complied during the crossover process in order to generate a feasible offspring individual. No available crossover method considers such constraints. Thus, specific RC crossover method is needed to generate better and feasible offspring individual from the two selected parent individuals.

The greedy crossover method is first applied to inherit the better tube connections from the parent individuals, and then RC generation method, which considers the tube connection constraints in practical RC, is used to uniformly generate the

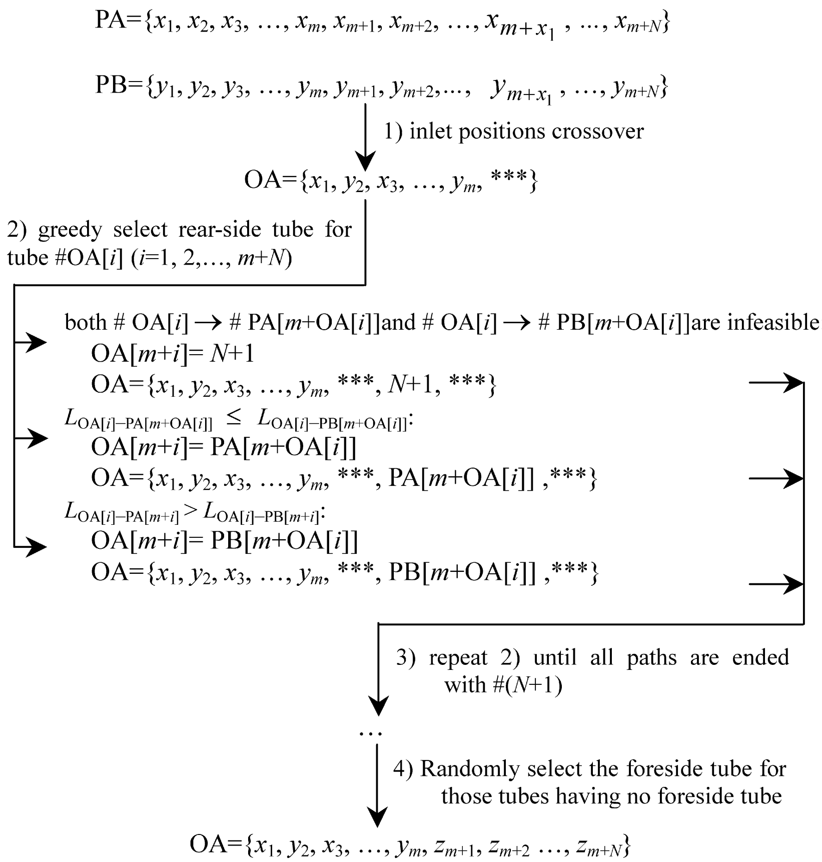


Fig. 2. Schematic of the greedy crossover method for RC optimization.

remaining tube connections in the offspring individual. Suppose the two selected parent individuals and their offspring are PA, PB and OA, respectively. In order to inherit the information of the inlet positions of the parent individuals, the greedy crossover operator alternately selects the inlet tubes of PA and PB as the inlet tubes of OA at first. Then, it greedily searches the rear-side tube starting from each inlet tube of OA until infeasible connections occur. More specifically, it starts with the inlet tube t of the 1st path of OA, and then checks whether same rear-side tube of t is used in both parent RCs. If so, the common rear-side tube is chosen. Otherwise, it compares t's rear-side joint tube length in each of the parents. For the goal of obtaining the shortest joint tubes, the shorter one is chosen unless an infeasible connection is introduced, in which case the longer one is chosen. If the longer one would also introduce an infeasible connection, set the rear-side tube of t as tube $\#(N+1)$. For the goal of obtaining the maximum heat transfer, one tube is randomly chosen unless an infeasible connection is introduced, in which case the other one is chosen. If the both tubes would also introduce an infeasible connection, set the right tube of t as tube $\#(N+1)$. Same steps performed on the 1st path are repeated on other paths, until all the paths are ended with the tube $\#(N+1)$. And then, it uniformly determines the foreside tube for those tubes without foreside tube until all tubes are connected into the RC. The benefit of our method is that the offspring has the priority to greedily inherit better genes from the two parent individuals, as well as the freedom to select other connections when there are no feasible connections that can be inherited from the parent individuals. Fig. 2 schematically shows the greedy crossover method for PA and PB.

3.5.1. Greedy mutation

The pure random RC mutation method easily generates infeasible tube connections as well as worse solutions. Too much time is cost for correcting the numerous infeasible tube connections in order to obtain a feasible RC solution, and the worse solutions may slow down the optimization progress. Therefore, new RC mutation methods are needed in order to reduce the optimization time.

The authors develop a greedy mutation method originally for RC optimization. The method divides the RC into several paths according to its tube connection topology at first, and then it randomly selects one path and randomly changes the tube connection order in the single path. This mutation method can greatly reduce the probability of generating infeasible solutions because the tube connection order is randomly changed only in one single path. As there is no iteration in calculating the total length of joint tubes of a fin-and-tube heat exchanger, the time for calculating the total length of joint tubes of a given RC is far less than that for calculating the heat exchange capacity. Therefore, for the goal of obtaining the shortest joint tubes, the computer calculates the total length of joint tubes of the RC after changing the tube connection order. If the new RC has shorter joint tubes, it replaces the original one and the mutation

$$\mathrm{PA}=\{x_1, x_2, \ldots, x_m, x_{m+1}, \ldots, x_{m+x_1}, \ldots, \underline{x_{m+j_2}}, \ldots, \underline{x_{m+i_2}}, \ldots, x_{m+N}\}$$

$\downarrow$ 1) divide the RC into several paths

$$\#0 \to \# x_1 \to \# x_{m+x_1} \to \# x_{m+i_1} \to \ldots \to \# x_{m+j_1} \to \ldots \to \#(N+1)$$
$$\#0 \to \# x_2 \to \# x_{m+x_2} \to \# \underline{x_{m+i_2}} \to \ldots \to \# \underline{x_{m+j_2}} \to \ldots \to \#(N+1)$$
$$\ldots$$
$$\#0 \to \# x_m \to \# x_{m+x_m} \to \# x_{m+i_m} \to \ldots \to \# x_{m+j_m} \to \ldots \to \#(N+1)$$

$\downarrow$ 2) randomly select one path

$$\#0 \to \# x_2 \to \# x_{m+x_2} \to \# \underline{x_{m+i_2}} \to \ldots \to \# \underline{x_{m+j_2}} \to \ldots \to \#(N+1)$$

$\downarrow$ 3) randomly change the tube order in the selected path

$$\#0 \to \# x_2 \to \# x_{m+x_2} \to \# \underline{x_{m+j_2}} \to \ldots \to \# \underline{x_{m+i_2}} \to \ldots \to \#(N+1)$$

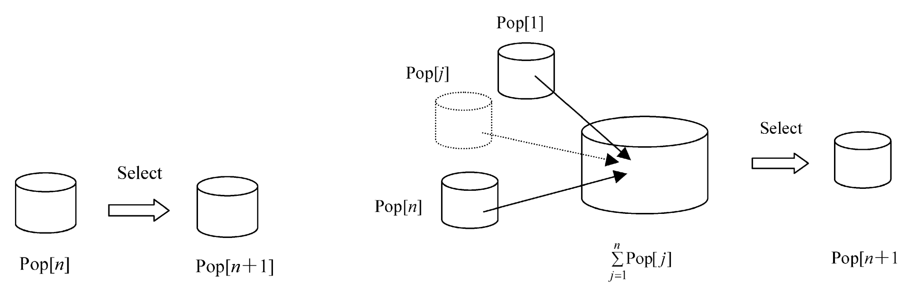
$\downarrow$ 4) obtain the offspring of OA

$$\mathrm{OA}=\{x_1, x_2, \ldots, x_m, x_{m+1}, \ldots, x_{m+x_1}, \ldots, \underline{x_{m+i_2}}, \ldots, \underline{x_{m+j_2}} \ldots, x_{m+N}\}$$

$\downarrow$

Repeat 2) – 4) until OA is better than PA or maximum mutation number is reached

Fig. 3. Schematic of the greedy mutation method for RC optimization.



(a) the existing selection method (CPSM) (b) the novel selection method (APPSM)

Fig. 4. Schematic of the mechanics of the selection method of CPSM and APPSM.

process ceases, otherwise the operation of randomly changing the tube connection order is repeated until a better solution is generated or the maximum number of repeat operations is reached. For the goal of obtaining the maximum heat transfer, this greedy mutation method can still be used, but the maximum number of repeat operations should not be very large in order to avoid a too long optimization time. Fig. 3 schematically shows the process of the greedy mutation operation for one selected RC solution. With this mutation method, the positions of inlet/outlet tubes and inner confluence/divergence tubes could also be changed, so it has the ability to enlarge the solution-search-space and to increase the possibility of finding the global optimal solution.

3.5.2. All-previous-population based selection

The selection method that can select both high diversity and high quality individuals for next generation may push forward the genetic process. But the existing current-population-based selection method (CPSM) has the drawback of losing better solutions during the genetic process. In fact, many individuals that may contain some useful genes are generated but not survived in the current population during the genetic process with CPSM. If these genes are considered during the selection of next generation population, the solution space may be extended and the efficiency of the optimization process may be improved.

An all-previous-population based selection method (APPSM) is developed in order to improve the diversity and quality of the individuals in the population of next generation. This selection method gives equal chances to all the individuals in all previous populations to be selected as the individuals of next generation. Therefore, it has higher possibility to select high-diversity and high-quality individuals. Figs. 4(a) and (b) schematically show the mechanics of the existing CPSM and our APPSM. The drawback of the APPSM compared with CPSM is that it costs more inner memory for storing the solutions. But it will not affect the running of the program because no more than 1 MB inner memories are needed after using one-dimensional integer string to represent the RC.

3.6. Fitness functions for RC optimization

Every solution in the population should be evaluated during the genetic optimization process. A fitness function is needed to rank the fitness value of each individual for selecting individuals to next generation. In order to effectively evaluate the solutions and guide the optimization process, different fitness functions are designed for different kind of optimization targets.

3.6.1. Fitness function for the goal of obtaining the shortest joint tubes

Eq. (2) is used as the fitness function for obtaining the shortest joint tubes:

$$F(j) = \delta\frac{L}{L_r} + (1-\delta)\frac{Q_0}{Q} \tag{2}$$

where $F(j)$ is the fitness value of the No. j solution in the population; L is the total length of joint tubes of the No. j solution in the population; L_r is the reference value of the total length of joint tubes, and can be set as the shortest total length of joint tubes of the solutions in the first generation; δ is the weight factor for balancing the effect of the total length of joint tubes and the heat exchange capacity of the solutions. Generally, δ is set as 0.6–0.9.

3.6.2. Fitness function for the goal of obtaining the maximum heat transfer

Eq. (3) is used as the fitness function for obtaining the maximum heat exchange capacity:

$$F(j) = 1.0/Q \tag{3}$$

3.7. Flow chart of the IGA for RC optimization

An improved genetic algorithm (IGA) for RC optimization is developed by organizing the above developed RC representation method, RC generation method, greedy crossover method, greedy mutation method, selection method and RC correction method together. In order to absolutely avoid the infeasible solutions to guarantee the stability of the optimization program, the correction operators are applied to check and correct the solutions after each genetic operation in the IGA. Fig. 5 shows the flow chart of the IGA. In order to show the difference between the IGA and the SGA, the added and improved parts in the IGA compared with those in the SGA are highlighted with different background in Fig. 5.

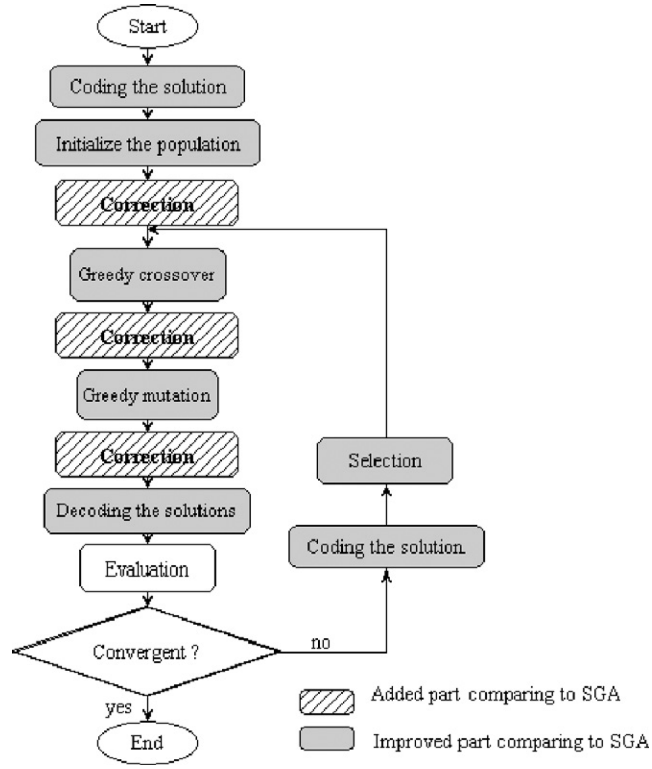


Fig. 5. Flow chart of the IGA for RC optimization.

4. Case study and discussion

It is better to make comparisons for each improvement of the IGA and the SGA in order to verify the IGA. In the IGA, the RC representation method, RC initialization method, RC correction method, crossover method, mutation method and selection method are developed or improved comparing with those in the SGA. The RC representation method, RC initialization method and RC correction method are originally developed in the IGA, and the simple GA may not be workable for RC optimization if the three methods are not applied. Therefore, the effect of the RC representation method, RC initialization method and RC correction method can be verified only if the IGA can perform a RC optimization smoothly. In order to verify the IGA behaviors with respect to the variation of external parameters of the heat exchanger, three test cases including evaporator and condensers with different scales are used to perform series of tests. The structural parameter and work conditions of the 3 test cases are shown in Table 1. In order to verify the effect of the greedy crossover method, greedy mutation method and APPSM selection method developed in the IGA, each test case is optimized with the following 3 methods: (1) the SGA only using pure random crossover, pure random mutation method and the proposed RC correction method, (2) the IGA with CPSM selection method and (3) the IGA with APPSM selection method.

The following parameters of GA are used in the tests: the population size is 10; the maximum generation number is 300; the crossover probability is 0.6; the mutation probability is 0.85; the selection model is Rank-based Model [16]; no specific initial RC solutions are given at the outset of the optimization; the convergence criterion is that the generation number reaches to the maximum value. The heat exchange capacity of RC solution is evaluated by using the improved heat exchanger simulation software based on Ref. [6], which can predict the heat transfer and pressure drop characteristics of heat exchangers using R410A with the deviations less than ±5% and ±15% respectively. The heat transfer model from Ref. [6] is summarized in Appendix A.

Table 1
Structural parameters and work conditions of the test cases

Structural parameters	Case 1	Case 2	Case 3
Length/Width/Height (mm)	900/726.6/7266	900/739.9/7266	900/736.4/7630
Row number/Tube number per row	2/12	3/12	2/30
Row pitch/Tube pitch (mm)	13.3/21	13.3/21	18.2/21
Bottom boundary space of each row (mm)		5.25, 15.75, 5.25	
Inlet path number/Outlet path number	4/2	4/2	4/4
Tube diameter, mm/Type		7.0/Enhanced	
Fin pitch, mm/Fin type	1.37/Slit	1.37/Slit	1.457/Wavy
Total length of joint tubes for practical designs before optimization (mm)	501	1117	1176
Work conditions			
Refrigerant type	R410A	R410A	R410A
Refrigerant condensation temperature (°C)	50	50	2.05
Refrigerant inlet superheat (°C)	11	11	–
Refrigerant inlet mass quality	–	–	0.232
Mean flow rate (g s^{-1})	22.14	22.14	28.54
Air inlet temperature Tdb/Twb (°C)	35/24	35/24	7/6
Air velocity (m s^{-1})	1.5	1.5	1.58
Minimum heat exchange capacity (W)	3500 × 0.95	3840 × 0.95	4870 × 0.95

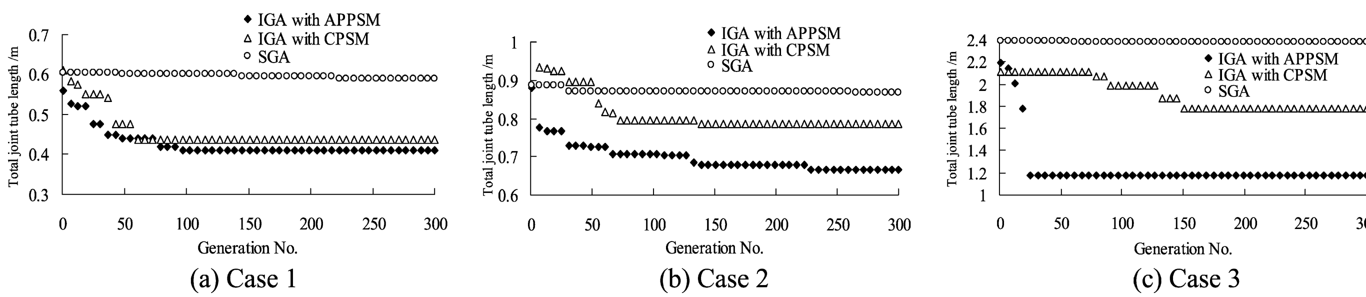


Fig. 6. Variation of the total length of joint tubes of the best individual in each generation for obtaining the shortest joint tubes.

4.1. Test results for the goal of obtaining the shortest joint tubes

Figs. 6(a)–(c) show the variation of the total length of joint tubes of the best individual in each generation during the optimization process for obtaining the shortest joint tubes for each case, respectively. It shows that (1) for all the test cases with different scales, both the optimization speeds and the optimal results of the IGA with APPSM and the IGA with CPSM are much better than those of the SGA; (2) both the optimization speeds and the optimal results of the IGA with APPSM are better than those of the IGA with CPSM.

The higher efficiency of the IGA comparing with that of the SGA is due to the use of the greedy crossover operator and greedy mutation operator in the IGA. In the SGA, only pure random crossover operation and mutation operation are applied, the new solutions generated by such operations may be worse than their ancestors, and there is no progress in the SGA if worse offspring are always generated. While in the IGA, greedy crossover operator and greedy mutation operator are applied, which can generate better offspring with higher probability and give an enhanced power to push forward the optimization process. Both the optimization speed and the optimal results of the IGA with APPSM are better than those of the IGA with CPSM because the APPSM gives equal chances to all the individuals in all previous populations to be selected as the individuals of next generation. Thus, it has higher possibility to select high-diversity and high-quality individuals for next generation, which improves the efficiency of the genetic process.

Figs. 7(a)–(c) show the variation of the heat exchange capacity of the best individual in each generation during the optimization process for obtaining the shortest joint tubes for Cases 1–3, respectively. The test results show that, with each optimization method, the heat exchange capacity of the best individual in each generation increases or decreases during the optimization process, even the total length of joint tubes always decreases during the optimization process. It is consistent with the fact that, under some working conditions, the heat exchange capacity of the heat exchanger is not proportional to the total length of the joint tubes because the RC pattern has more powerful effect on the heat transfer performance. The variations shown in Figs. 6 and 7 also denote that a RC with shorter joint tubes may still have the ability to obtain higher heat exchange if the RC is well designed.

For the target of obtaining the shortest joint tubes, the mean value of the total length of joint tubes of all the individuals in each generation represents the quality of the population. Figs. 8(a)–(c) show the variations of the mean value of the total length of joint tubes of the individuals in each generation for Cases 1–3, respectively. It shows that, for each case, (1) the IGA with APPSM provides the lowest mean value of the total length of joint tubes in each generation; (2) the mean value of the total length of joint tubes in each generation of

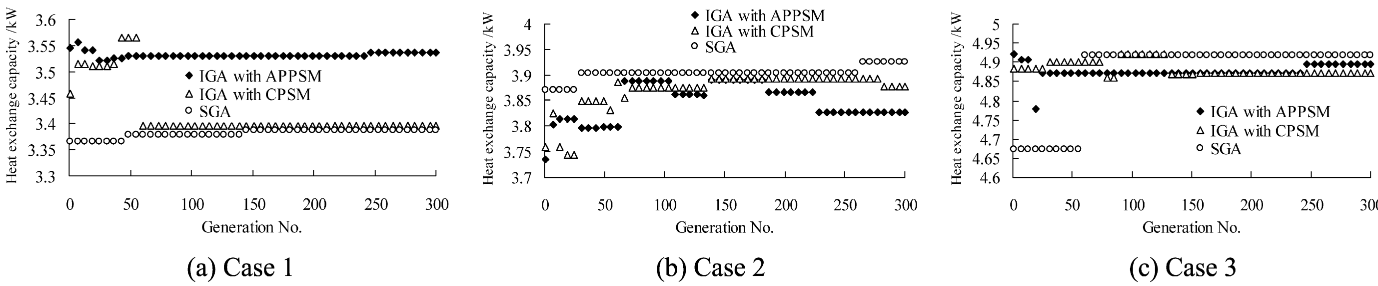


Fig. 7. Variation of the heat exchange capacity of the best individual in each generation for obtaining the shortest joint tubes.

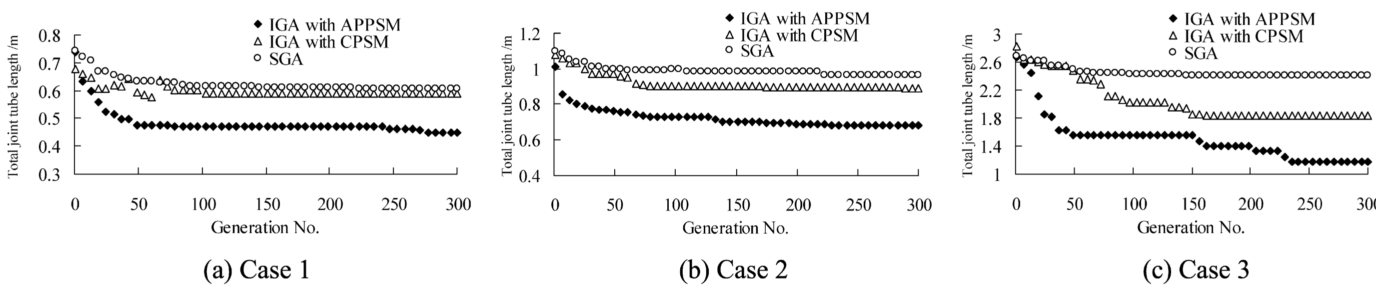


Fig. 8. Variation of the mean total length of joint tubes of all individuals in each generation for obtaining the shortest joint tubes.

the IGA with APPSM varies more frequently than those of the SGA and the IGA with CPSM. These test results prove that the IGA with APPSM has higher ability to change the diversity and quality of the individuals in each generation, which greatly contributes to the higher optimization ability of the IGA with APPSM.

Figs. 9(a)–(c) show the optimal solutions obtained by the IGA with APPSM for obtaining the shortest joint tubes for Cases 1–3, respectively. It can be found that (1) most of the connections are placed between adjacent tubes in order to shorten the total joint tube length; (2) all the connections on the far side of the heat exchanger are between adjacent tubes which make it be possible for the manufacturers to insert the hairpins from the far side of the heat exchanger to improve the efficiency of manufacturing the heat exchangers; (3) the refrigerant outlets are located in the front row and far away from the inlets, which contributes to higher heat exchange capacity. The calculation results show that the heat exchange capacity of the optimal RCs for Cases 1–3 are 3532 W, 3827 W and 4901 W, respectively, which satisfy their minimum requirements on heat exchange capacity. The total length of joint tubes of the optimal RCs for Cases 1–3 are 410.3 mm, 666.1 mm and 1176.0 mm, which are 26.60%, 24.4% and 46.3% shorter than the initial ones during the optimization, and are 18.1%, 40.3% and 0% shorter than those of the practical designs before optimization as shown in Table 1. A 0% decrease in Case 3 comparing with the practical designs before optimization is mainly because the practical designs before optimization are also the best human designs. The test results denote that the IGA is suitable for heat exchanges with different scales and has the ability to automatically provide RC solutions equal or superior to those designed by human.

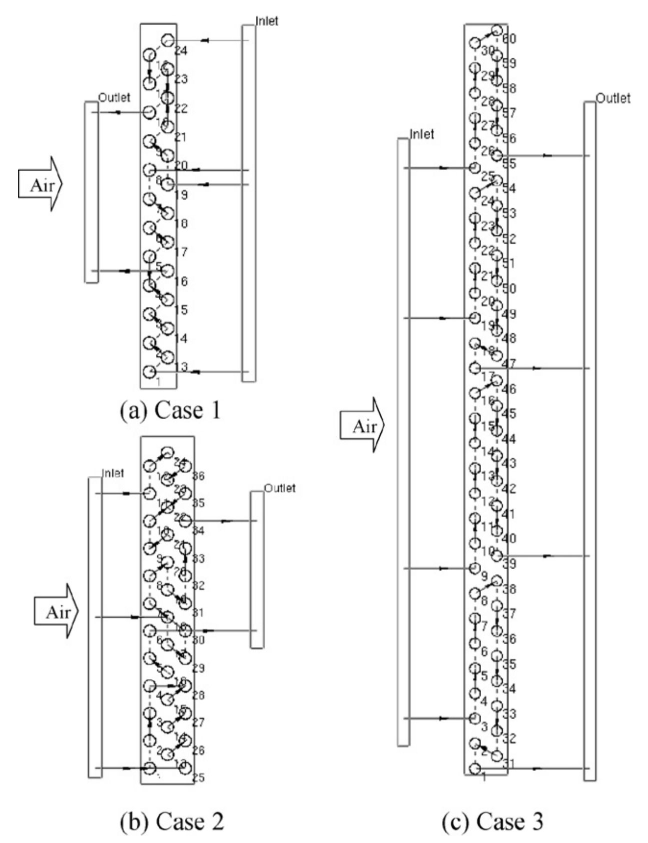


Fig. 9. Optimal solutions obtained by the IGA with APPSM for obtaining the shortest joint tubes.

4.2. Test results for the goal of obtaining the maximum heat transfer

Figs. 10(a)–(c) show the variation of the heat exchange capacity of the best individual in each generation during the op-

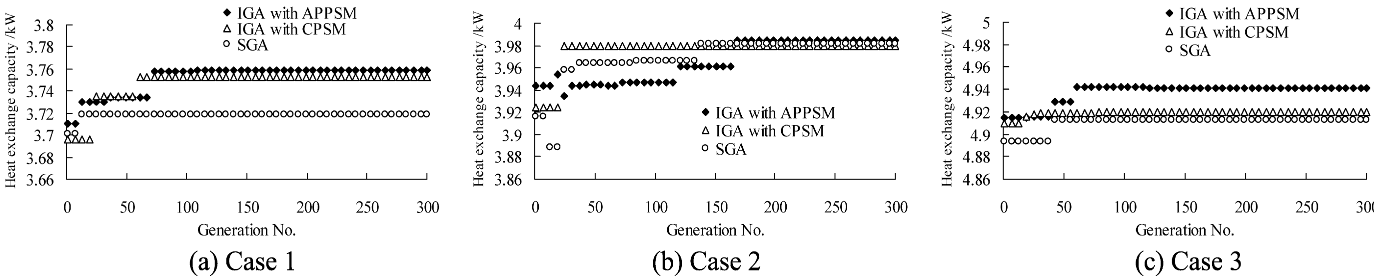


Fig. 10. Variation of the heat exchange capacity of the best individual in each generation for obtaining the maximum heat transfer.

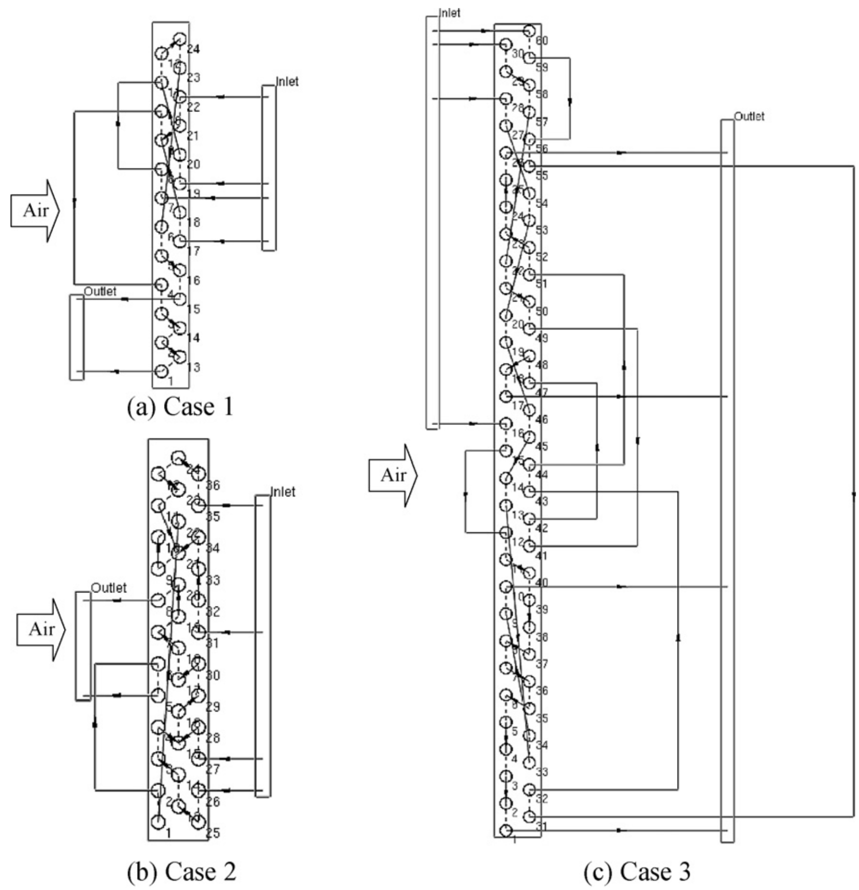


Fig. 11. Optimal solutions obtained by the IGA with APPSM for obtaining the maximum heat transfer.

timization process for obtaining the maximum heat transfer by using the SGA, the IGA with APPSM and the IGA with CPSM for Cases 1–3, respectively. It shows that the heat exchange capacity of the best individual in each generation increases during the optimization process. For each case, both the optimization speeds and the optimal results of the IGA with APPSM and the IGA with CPSM are better than those of the SGA. However, the improvement degree of the obtained maximum heat exchange capacity with different optimization methods is not very large. This is mainly because the crossover operation in the IGA for the target of obtaining the maximum heat transfer is random operation, and the impulse of obtaining higher efficiency of the IGA mainly depends on the greedy mutation operation. Therefore, more powerful genetic operators are needed for the target of obtaining the maximum heat transfer.

Figs. 11(a)–(c) show the optimal solutions obtained by the IGA with APPSM for obtaining the maximum heat transfer for Cases 1–3, respectively. It can be found that (1) almost all the refrigerant outlets locate on the front row, which enhances heat transfer between air and refrigerant in the outlet tubes by increasing the temperature difference between the two fluids; (2) almost all the refrigerant outlets and inlets are far away from each other, which can reduce the heat conduction loss via the continuous fin between the refrigerant inlets and outlets, therefore the heat exchange capacity can be increased; (3) all the connections on the far side of the heat exchanger are between adjacent tubes which make it be possible for the manufacturers to insert the hairpins from the far side of the heat exchanger to improve the efficiency of manufacturing; (4) some connections on the near side of the heat exchanger span over several tubes, which can help to adjust the air flow exposed on each path by selecting suitable tubes to the path in order to obtain identical refrigerant state at the outlet of each path. It looks difficult to manufacture some connections spanning over tubes at first glance, but it is feasible and may not increase much cost for the manufacturers to realize these connections since all tubes are already located in the heat exchanger by inserting hairpins to the heat exchanger from it far side. The test results show that the heat exchange capacity of the optimal RCs for Cases 1–3 are 3759 W, 3984 W and 4941 W, which are 7.4%, 3.8% and 2.8% higher than those practical designs before optimization, respectively. It also shows that the improvement degree of the heat exchange capacity in the optimal solutions decreases when the scale of the heat exchangers increases. The main reason for this phenomenon is that the number of possible solutions increases rapidly with the increase of the scale of the heat exchangers, which may decrease the chance to find the optimal solutions within same number of search times. Increasing the search times or developing more powerful genetic operators is possible way to overcome this problem.

The optimization time depends on the population size, total generation number and the time to evaluate each individual of the test case during the optimization process. It takes about 11 s, 16 s, and 14 s to evaluate one individual of Cases 1–3 on a computer with Pentium (R) CPU 2.66 GHz and 1 GB RAM, respectively. The test results show that the optimization time of each test case with the methods of the SGA, the IGA with CPSM and the IGA with APPSM are almost the same and less than 15 h, which can satisfy the requirements of the practical engineers to start the optimization before leaving the office for home on one day and to obtain the optimization results on next morning.

5. Conclusions

This paper presents a novel approach for optimizing the RC of fin-and-tube heat exchangers based on the genetic algorithm. The new RC representation method is developed and can save both computer memory and decoding time. RC correction operators are used to absolutely avoid the infeasible solutions without shrinking the searching space. New RC generation method, greedy crossover method, greedy mutation method and APPSM selection method are used to improve the efficiency of the RC optimization process.

Serial tests are performed on three test cases with different scales for obtaining the shortest joint tubes and for obtaining the maximum heat transfer, respectively. The following conclusions can be obtained according to the test results: (1) the GA is suitable for optimizing the refrigerant circuit of fin-and-tube heat exchanger with the developed RC representation method, RC initialization method and RC correction method; (2) the improved greedy crossover method and greedy mutation method have higher efficiency than the traditional genetic operators for RC optimization; (3) the selection method based on all previous populations is better than the selection method only based on current population in the genetic process; (4) the IGA has the ability to automatically provide RC solutions equal or superior to those designed by human.

This approach extends the GA application range to the RC optimization of fin-and-tube heat exchangers, and introduces a simpler and more effective method for practical RC optimization. The developed selection method based on all previous populations can contribute to improve the efficiency of the optimization process using GA. Further studies are still needed to develop more effective genetic operators to improve the optimization efficiency for obtaining maximum heat transfer. Applying heat transfer theories to guide the crossover or mutation operation may be a promising way to develop higher efficient IGA for obtaining maximum heat transfer.

Appendix A

The refrigerant flow inside the tube is considered as one-dimensional axial flow and the axial conduction along the tubes is neglected.

Energy conservation equation for refrigerant flow in tubes:

$$Q_{1\mathrm{r}} = Q_{2\mathrm{r}} \tag{A.1}$$

where

$$Q_{1\mathrm{r}} = M_\mathrm{r}(h_{\mathrm{r,in}} - h_{\mathrm{r,out}}) \tag{A.2}$$

$$Q_{2\mathrm{r}} = \alpha_\mathrm{r} A_\mathrm{i}\left(\frac{T_{\mathrm{r,in}} + T_{\mathrm{r,out}}}{2} - T_{\mathrm{wall}}\right) \tag{A.3}$$

here α_r is calculated from selected empirical correlations.

Continuity equation for refrigerant flow in tubes:

$$G_{\mathrm{r,out}} = G_{\mathrm{r,in}} \tag{A.4}$$

Momentum conservation equation for refrigerant flow in tubes:

$$\Delta p_{\mathrm{r,tube}} = \Delta p_{\mathrm{r,f}} + \Delta p_{\mathrm{r,acc}} \tag{A.5}$$

where $\Delta p_{\mathrm{r,f}}$ and $\Delta p_{\mathrm{r,acc}}$ are calculated from selected empirical correlations.

Energy conservation equation for air:

$$Q_{1\mathrm{a}} = Q_{2\mathrm{a}} \tag{A.6}$$

where

$$Q_{1\mathrm{a}} = M_\mathrm{a} \cdot (h_{\mathrm{a,in}} - h_{\mathrm{a,out}}) \tag{A.7}$$

$$Q_{2\mathrm{a}} = \alpha_\mathrm{a} A_\mathrm{o} \eta_\mathrm{o}\left(\frac{T_{\mathrm{a,in}} + T_{\mathrm{a,out}}}{2} - T_{\mathrm{wall}}\right) \tag{A.8}$$

here air mass flow rate M_a is calculated based on upstream control volumes in front row; α_a is calculated from selected empirical correlations.

Continuity equation for air:

$$G_{\mathrm{a,out}} = G_{\mathrm{a,in}} \tag{A.9}$$

Momentum conservation equation for air:

$$\Delta p_\mathrm{a} = \Delta p_{\mathrm{a,fin}} + \Delta p_{\mathrm{a,tube}} \tag{A.10}$$

where $\Delta p_{\mathrm{a,fin}}$ is the airside pressure drop due to the fin surface; $\Delta p_{\mathrm{a,tube}}$ is the airside pressure drop due to the tube surface.

The energy conservation equation for fin-and-tube:

$$Q_{1r} + Q_{1a} + Q_{cond} = 0 \tag{A.11}$$

$$Q_{cond} = Q_{front} + Q_{back} + Q_{top} + Q_{bottom} \tag{A.12}$$

where Q_{cond} is the total heat conduction by fins; Q_{front}, Q_{back}, Q_{top}, and Q_{bottom} are heat conductions by fins from nearest front row, back row, upper column, and bottom column, respectively.

For coil with divergence or confluence, the governing equations at the divergence or confluence points are needed in order to determine the inlet state parameters of refrigerant in downstream branches. Eqs. (A.13)–(A.15) are used for No. i divergence flow.

$$M_{r,in} = \sum M_{r,ij} \quad (j = 1, 2, \ldots, m) \tag{A.13}$$

$$h_{r,in} = h_{r,ij} \quad (j = 1, 2, \ldots, m) \tag{A.14}$$

$$p_{r,in} = p_{r,ij} \quad (j = 1, 2, \ldots, m) \tag{A.15}$$

where $M_{r,in}$, $h_{r,in}$ and $p_{r,in}$ are the mass flow rate, specific enthalpy and pressure of refrigerant at the inlet of the of No.'i' divergence, respectively; $M_{r,ij}$, $h_{r,ij}$ and $p_{r,ij}$ are the mass flow rate, inlet specific enthalpy and inlet pressure of refrigerant in No. "j" branch of No.'i' divergence, respectively.

The following equations are used for No. i confluence flows:

$$M_{r,i} = \sum_{j=1}^{m} M_{r,ij} \quad (j = 1, 2, \ldots, m) \tag{A.16}$$

$$h_{r,i} = \frac{\sum_{j=1}^{m} h_{r,ij} M_{r,ij}}{\sum_{j=1}^{m} M_{r,ij}} \quad (j = 1, 2, \ldots, m) \tag{A.17}$$

$$p_{r,i} = p_{r,ij} \quad (j = 1, 2, \ldots, m), \tag{A.18}$$

where $M_{r,i}$, $h_{r,i}$ and $p_{r,i}$ are the mass flow rate, specific enthalpy and pressure of refrigerant at the point after the of No.'i' confluence; $M_{r,ij}$, $h_{r,ij}$ and $p_{r,ij}$ are the mass flow rate, inlet specific enthalpy and inlet pressure of refrigerant in the No. 'j' subpath of No.'i' confluence.

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