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Tube-Fin Heat Exchanger Circuitry Optimization Using Integer Permutation Based Genetic Algorithm

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ABSTRACT

Tube-fin heat exchangers (HXs) are widely used in air-conditioning and heat pump applications. The performance of these heat exchangers is strongly influenced by the refrigerant circuitry, i.e. the refrigerant flow path along the different tubes in the HX core. Since for a given number of tubes, the number of possible circuitries is exponentially large, neither the exhaustive search nor traditional optimization algorithms can be used to optimize the circuitry for a given application. Researchers have previously used Genetic Algorithms (GAs) coupled with a learning module or other heuristic algorithm to solve this problem, but there is no guarantee that the resulting circuitry can be manufactured in a cost-effective manner. In this paper, we present an integer permutation-based GA approach for solving the circuitry optimization problem. A finite volume heat exchanger simulation tool is used to simulate the performance of different circuitries generated by the optimizer. The novel genetic operators are designed such that all chromosomes generated by GA can be mapped to a valid circuitry design. As a result, the proposed approach can explore the solution space more efficiently than a conventional GA. The manufacturability aspect is handled using a constraint-dominated sorting technique in the fitness assignment stage. The analyses of several case studies show that the constrained integer permutation-based GA can generate circuitry designs with capacities superior to those obtained manually and meanwhile guarantee good manufacturability. Overall, a 2.4-14.6% increase in heat exchange capacity is observed by applying the new optimization method to an evaporator from a A-type indoor unit. Comparison with other optimization methods in literature shows that the proposed approach exhibits higher quality optimal solutions than other methods.

1. INTRODUCTION

Tube-fin heat exchangers (TFHXs) are the prominent component in air conditioner and heat pump applications. This type of heat exchanger consists of a bundle of tubes which protrude into fin sheets. The performance of TFHXs is greatly affected by a large number of structural parameters (tube diameter, tube length, fin type, fin thickness, etc.). Therefore, optimization of heat exchanger can significantly improve its performance (Huang *et al.*, 2015). For a TFHX, refrigerant flowing paths are defined by tube connections, i.e. refrigerant circuitry. The configuration of tube connections has significant impact on heat exchanger performance (Chwalowski *et al.*, 1989; Wang *et al.*, 1999; Bigot *et al.*, 2000; Liang *et al.*, 2001). To improve the performance of TFHX, performing optimization on refrigerant circuitry is more convenient and cost saving than varying other structural parameters.

Currently, design engineers usually choose refrigerant circuitry based on their experience or the benchmark result of a limited number of simulations for a few artificially designed circuitries. For instance, one of the most common circuitry pattern is the crossflow design in which refrigerant and moist air flow in opposite directions. There is no guarantee that manually designed circuitries are optimal designs, especially for large HXs. The circuitry optimization problem is particularly challenging due to the high nonlinearity between the circuitry and TFHX performance as well as the extremely large design space whose size increases exponentially with the increase of tube numbers. Taking a 10-tube TFHX as an example, just the 1-circuit design without merging or splitting has 10! (3,628,800) possibilities, not mention taking multiple-circuit designs, merging and splitting into consideration.

In recent years, researchers have developed several different approaches to solve TFHX circuitry optimization problem. Early research in this field started out with manual performance comparison of pre-defined circuitries and later leading to the use of more sophisticated optimization techniques such as heuristic algorithms. Liang *et al.* (2000) and Liang *et al.* (2001) firstly developed a HX model to evaluate performance of different circuitries based on exergy destruction, they compared six different circuitry designs and found the best circuitry can reduce the HX material by about 5% meanwhile maintaining the same performance as baseline. Since they only evaluated a small number of designs, their best circuitry is not necessarily the optimal. Domanski *et al.* (2004) developed an optimization model called ISHED (intelligent system of heat exchanger design). This optimization scheme switches between Evolutionary Learning and Symbolic Learning modules. In their subsequent publications (Domanski *et al.*, 2005; Domanski and Yashar, 2007; David Yashar *et al.*, 2010; Domanski *et al.*, 2011; David A Yashar *et al.*, 2012; David A Yashar *et al.*, 2015; Cho and Domanski, 2016), they applied this optimization scheme on condensers and evaporators, multiple working fluids, uniform and non-uniform airflow distribution, and conducted experimental validation for the optimal circuitry on heat exchanger level and cycle level. As a result, their experimental validated optimal circuitries offer superior heat exchanger capacity to that of manually designed circuitries. The maximum reported HX capacity improvement from optimization runs and experimental validation are 6.5% and 2.2% respectively. Wu *et al.* (2008a) and Wu *et al.* (2008b) developed another optimization approach, which also switches between two optimization methods, i.e. knowledge-based GA and Simulated Annealing model. In order to speed up optimization, they created effective operators (greedy crossover and greedy mutation). The maximum predicted capacity improvement in their study is 7.4%. More recently, Lee *et al.* (2016) proposed an analytical method to determine the optimal number of circuits for tube-fin condensers, this method uses exergy destruction as criterion to assess HX performance. Ploskas *et al.* (2017) represented circuitry by adjacency matrix and constrained the hairpins to be on one side of the HX. By comparing five different derivative-free optimization algorithms, they concluded that TOMLAB/glcDirect and TOMLAB/glcSolve can find optimal or near-optimal circuitries more efficiently. However, in their study, the performance improvement is not reported quantitatively. Bahman and Groll (2017) proposed an interleaved circuitry for evaporators operating under airflow maldistribution. Variations of interleaved circuitries have been used in the industry for over a decade. Their results show that the interleaved circuitry method can yield uniform superheat at the outlet of the individual circuits and can improve the cooling capacity and cycle COP by up to 16.6% and 12.4% respectively under airflow maldistribution case compared with a baseline HX without interleaved circuitry.

The TFHX circuitry optimization problem has a large and discrete design space. This kind of problems are usually classified as combinatorial optimization problem (Gray *et al.*, 1997). Examples of combinatorial optimization problems include but are not limited to Travelling Salesman Problem (TSP), Vehicle Routing Problem (VRP), Minimum Spanning Tree Problem (MST). In the field of optimization, there are two groups of optimization methods, classic methods and Evolutionary Algorithms (Deb, 2012). The classic methods use a single solution update in every iteration and use a deterministic procedure to approach the optimal solution. While the Evolutionary Algorithms (EAs) simulate natural evolutionary processes and involve stochastic optimization techniques. For combinatorial problems, EAs often outperform classic methods (Gen *et al.*, 2008). Evolutionary Algorithms such as Genetic Algorithms, Evolutionary Programming, Evolution Strategies, Genetic Programming, Learning Classifier Systems, Swarm Intelligence (including Ant Colony Optimization) and Particle Swarm Optimization have been extensively used to solve complex combinatorial problems (Gen *et al.*, 2008). Among them, Genetic Algorithm (Holland, 1992) mimics the principles of natural genetics and natural selection and is extensively used in various problem domains due to its broad applicability, ease of use and global search (Goldberg, 1989).

In this paper, Genetic Algorithm is used to solve tube-fin heat exchanger circuitry optimization problem. A finite volume heat exchanger model, CoilDesigner® (Jiang *et al.*, 2006) is used to simulate the performance of TFHX with different circuitries. The primary contribution of this paper is to present a new integer permutation-based GA approach. This new approach can generate valid circuitry designs without requiring extensive domain knowledge. Manufacturing constraints are incorporated to guarantee that the optimal designs are manufacturable.

The remainder of the paper is organized as follows. Section 2 details the new optimization approach. Section 3 presents the methods to handle manufacturing constraints. Section 4 demonstrates the efficiency of the proposed approach through multiple case studies. Section 5 compares the performance of the new approach with other methods in literature. Conclusions of this study are drawn in Section 6.

2. INTEGER PERMUTATION BASED GENETIC ALGORITHM

2.1 Representation of HX Circuitry

A good individual representation (chromosome) can not only improve the efficiency of genetic algorithm by reducing the searching space, but it should be easy to interpret by simulating the nature of the problem (Deb, 2012). It has been shown that a meaningful and appropriate chromosomal representation of the problem can speed up Genetic Algorithm to converge to a global optimal (Kargupta *et al.*, 1992). For tube-fin heat exchanger circuitry optimization problem, the proposed approach represents tubes in circuit as a sequence of integers, where each integer represents a tube in a given flow path. The optimization technique is independent of the actual numbering of the tubes. For an integer permutation, each integer (i.e., tube number) appears exactly once, thus, any chromosome generated by the Genetic Algorithm can be mapped to a valid circuitry and the size of the search space is dramatically reduced by the elimination of redundant designs. It needs to be mentioned that merging or splitting is not allowed in the scope of this paper. A future version of this framework presented in a subsequent paper will support merging and splitting and explore their potential to improve HX performance.

Two different chromosome representations are developed and implemented in the new optimization framework. Consider a 15-tube, 4-circuit HX as an example (shown in Figure 1(a)). The red circle indicates the inlet refrigerant streams and blue circle indicates the outlet refrigerant streams. A solid line represents a U-bend on the front end, while a dotted line represents a U-bend on the farther end of the heat exchanger.

The first type of chromosome is called a “Two-Part Chromosome” as shown in Figure 1(b), in which the first part denotes tube sequences, the second part denotes the number of tubes in each circuit. This type of chromosome works well when optimal number of circuits can be determined before conducting the optimization, using preliminary analysis such as the one presented in (Lee *et al.*, 2016) or using rules of thumb or application specific knowledge. However, in majority of the applications, especially for new product designs, the optimal number of circuits cannot be easily derived, and a more generic representation is desired. This necessitates the ‘Split Circuit Chromosome’ as shown in Figure 1(c). The Split Circuit Chromosome uses the concept of jagged arrays, each element of this array is the tube sequence in each circuit and can contain variable number of tubes. With Split Circuit Chromosome, number of circuits is flexible, i.e., the optimal number of circuits is also an output from optimization. Intuitively, Split Circuit Chromosome represents a refrigerant circuitry in a more realistic manner because it “physically” separates different circuits from each other.

Figure 1: Circuitry Representation: (a) 15-tube TFHX; (b) Two-Part Chromosome; (c) Split Circuit Chromosome

2.2 Selection

The selection operator, selects superior individuals in a population and forms a mating pool. The common selection methods from Genetic Algorithm literature are tournament selection, proportionate selection (i.e. Roulette wheel selection) and ranking selection (Goldberg, 1989). The essential idea is to pick the above-average individuals from the current population and insert duplicates of those elite individuals in the mating pool in a probabilistic manner. In this paper, a tournament selection operator with tournament size 2 is used along with an efficient constraint handling method which will be explained in section 3.2. Goldberg and Deb (1991) have shown that the tournament selection has better and equivalent convergence and computational time complexity properties compared with other selection operators in literature.

2.3 Crossover & Mutation Operators

The selection operator selects good individuals, while the creation of new individuals relies on the genetic operators. Conventional Genetic Algorithm uses crossover and mutation operators. There exist a number of crossover and mutation operators (Spears and Jong, 1998). For the conventional crossover operator, two individuals are picked from the mating pool at random and some portion of their chromosomes are exchanged to create two new individuals. Since the chromosomal representation of heat exchanger circuitry has the characteristic that each integer appears exactly once, it is obvious that exchanging genes among two individuals will undermine the structure of integer permutation, that is, it will make the new chromosome invalid to map to a circuitry. Coit and Smith (1996) has shown that constraint handling method such as penalty method cannot efficiently avoid the infeasible individual if Genetic Algorithm generates too many infeasible individuals than feasible ones and the optimization process will remain stagnant. For these reasons, the integer permutation-based chromosome necessitates new genetic operators.

In this study, six novel genetic operators are invented. These six genetic operators are classified into two groups, ‘in-circuit operators’ and ‘cross-circuit operators’. The first set manipulate tubes (i.e. genes) inside one randomly selected circuit, while the latter set manipulates tubes across different circuits. By transforming the selected individual to a new individual with potentially better fitness, these Genetic Algorithm operators direct the search and impel the optimization process.

The ‘gene sequence inversion’ operator as shown in Figure 2(a) chooses a random subsection of a circuit and inverts the order of the tubes inside it. The ‘gene transposition’ operator as shown in Figure 2(b) reverses two randomly chosen tubes inside a circuit. The ‘gene translocation’ operator as shown in Figure 2(c) put a randomly chosen tube into a random position. The ‘circuit union’ operator as shown in Figure 2(d) chooses two circuits and unite them into one circuit. The ‘circuit detachment’ operator as shown in Figure 2(e) is an inverse operation of ‘circuit union’ operator, it can split a given circuit into two circuits. It is obvious that ‘circuit union’ operator and ‘circuit detachment’ operator can vary the number of circuits such that number of circuits can be optimized in a generic fashion. Lastly, the ‘cross-circuit transposition’ operator as shown in Figure 2(f) randomly chooses subsections from two circuits then performs transposition.

Figure 2: Genetic Operators: (a) (b) (c) In-circuit operators; (d) (e) (f) Cross-circuit operators

3. CONSTRAINT HANDLING

For an optimization problem, constraints can be set on any inputs (design variables) and/or any outputs including the objective values. For tube-fin circuitry optimization problem, it is crucial to guarantee that the resulting circuitry can

be manufactured in a cost-effective manner, meanwhile handle these constraints in an efficient way. These two aspects are discussed in detail.

3.1 Manufacturability Constraints

Three manufacturing (mfg.) constraints are incorporated in the new method. These constraints are typically set by the user of the algorithm at the beginning of optimization.

1. **Inlets and outlets on the same side of HX:** Figure 3(a) shows a design, of which inlets and outlets are on the same side of HX. Figure 3(b) shows an undesirable design in which inlets and outlets are located on opposite sides.
2. **Limit or avoid long U-bends:** The longest allowed tube connection is defined as a U-bend stretching across more than two tube rows. In Figure 3(c), the tube connection highlighted in green ellipse stretches the maximum allowed distance, while the two long U-bends highlighted in red ellipses will be avoided in the current framework.
3. **Limit or avoid U-bend crossovers:** There are three different types of U-bends crossovers. As shown in Figure 3(d), 'full overlap' in yellow caption indicates two collinear U-bends, in which one U-bend is located above the other. 'Partial overlap' in red caption indicates two collinear U-bends which are partially overlapped. 'U-bend crossing' in blue caption indicates two intersected U-bends. Among the three kinds of U-bend crossovers, partial overlapped collinear U-bends may be the least preferred type from manufacture point of view.

Figure 3: Illustration for Manufacturing Constraints: (a) Inlets & outlets on the same side; (b) Inlets & outlets on the opposite sides; (c) Long U-bends; (d) Three kinds of U-bend crossovers

3.2 Constraint Handling Methods

The proposed framework uses an efficient constraint handling technique which is called constraint dominated sorting (Deb, 2000). This constraint handling method shows superior performances than the conventional penalty method in two aspects. Firstly, the efficiency of penalty method depends on the premise that the penalty parameter must maintain the same order of magnitude as the objective value which is not practical in various optimization problems. Secondly, it can lead to artificial optima, because the penalty term changes the formula of the objective function (Deb, 2012). The advantages of constraint dominated sorting include that it doesn't use any artificial penalty parameter, and it accounts for the degree of infeasibility (i.e. the extent of constraint violations). It follows these principles (Deb, 2000):

1. In a given population, any feasible individual is preferred over infeasible one.
2. Between two feasible individuals, the one having better objective value is preferred.
3. Between two infeasible individuals, the one having lower constraint violation is preferred.

4. CASE STUDY

4.1 Baseline Heat Exchanger

This section represents a case study to demonstrate the efficacy of the proposed optimization framework. An evaporator from an A-type indoor unit is used as the baseline for circuitry optimization. Table 1 shows the structural parameters and operating conditions for the baseline evaporator. Table 2 lists the empirical correlations used for local heat transfer and pressure drop calculations during the performance simulation of this evaporator.

Table 1: Structural Parameters and Operating Conditions of Baseline Evaporator

Structural Parameters	Value	Operating Conditions	Value
Tube Outer Diameter	9.5 mm	Refrigerant	R410A
Fins per inch	15 FPI	Refrigerant Inlet Pressure	1154.5 kPa
Fin Type	Wavy Louver	Refrigerant Inlet Quality	0.22
Tube Length	0.503 m	Refrigerant Mass Flow Rate	0.0312 kg/s
Vertical Spacing	20.0 mm	Air Volume Flow Rate (Uniformly Distributed)	600 ft ³ /min
Horizontal Spacing	25.0 mm	Air Pressure	101.325 kPa
Number of Tube Banks	4	Air Temperature	26.42 °C
Number of Tubes Per Bank	22	Air Relative Humidity	50.97 %

Table 2: Correlations Adopted in HX Simulation

Operating Mode	Heat Transfer Correlations	Pressure Drop Correlations
Refrigerant - Liquid Phase	Dittus and Boelter, 1985	Blasius, 1907
Refrigerant - Two Phase	Jung <i>et al.</i> , 1989	Jung and Radermacher, 1989
Refrigerant - Vapor Phase	Dittus and Boelter, 1985	Blasius, 1907
Air	Wang <i>et al.</i> , 1998	Wang <i>et al.</i> , 1998

The baseline as shown in Figure 4(a) has 4 circuits denoted in different colors. Majority of U-bends connect adjacent tubes in vertical direction, while there are 2 long U-bends at the middle height position of this HX, both long U-bends stretch across 3 tube rows. There are several U-bend crossovers. A finite volume heat exchanger model, CoilDesigner® (Jiang *et al.*, 2006) is used to simulate the performance of TFHX with different circuitries. This model was validated with measured data for this evaporator (Alabdulkarem *et al.*, 2015) and the deviation in cooling capacity between simulations and experiments are below 5% as shown in Figure 4(b). In this case study, the airflow distribution is assumed as uniform. Li *et al.* (2018) presents a separate study on circuitry optimization under airflow maldistribution.

Figure 4: (a) Baseline Circuitry; (b) Experiment Tests vs CoilDesigner® Simulations

4.2 Objectives

As discussed in Huang *et al.* (2015), various performance metrics have been used as objectives and constraints in heat exchanger optimization formulations. In the context of TFHX circuitry optimization, three types of objective have been used by previous investigators, as follows:

1. Maximize HX capacity (Domanski *et al.*, 2004; Wu *et al.*, 2008b; Ploskas *et al.*, 2017).
2. Minimize the total length of U-bends (Wu *et al.*, 2008a).
3. Maximize the ratio of heat capacity to refrigerant pressure drop (Ploskas *et al.*, 2017).

The proposed optimization framework supports various objective functions including the three aforementioned ones. In this case study, the capacity is maximized to demonstrate the capability of the proposed method.

4.3 Unconstrained Optimization

The first optimization is performed on an unconstrained problem with the goal of maximizing HX capacity. In all the optimization practices performed in this section, the population size is 200 and the number of generations is 500. Figure 5(a) shows the GA progress. Figure 5(b) shows the optimal circuitry. In the first 39 generations, the cooling capacity dramatically increases, as the number of circuits quickly drops to 1. Figure 5(c) shows a histogram of the number of circuits for all the designs evaluated in this optimization. Among a total of 100,000 evaluations, over 96% runs are successful. As can be observed from Figure 5(c), the GA evaluated a wide range of number of circuits (from 1- to 22-circuits), where 22 is the number of tubes per row. Since the coils with fewer circuits outperform the coils with more circuits, GA tends to converge to 1-circuit design. However, circuits union operator can transform 2-circuit design into 1-circuit design, while circuit detachment operator can modify 1-circuit design to be 2-circuit design. Therefore in later stage of this optimization run, individuals oscillate between 1-circuit and 2-circuit designs.

From Figure 5(a), the unconstrained optimization yields an optimal circuitry with a capacity increase from 5094 W to 6065 W by 14.6%. While the refrigerant pressure drop increases from 11.8 kPa to 972.5 kPa by 8800% due to the increase in mass flux and total flow path length. In addition to the undesirable large pressure drop, the optimal circuitry has several long U-bends and U-bend crossovers, which make it very challenging and costly to manufacture.

Figure 5: (a) Optimal circuitry; (b) GA optimization progress; (c) Histogram of number of circuits

4.4 Constrained Optimization

In order to address the above mentioned concerns, different combinations of constraints are introduced in the optimization problem. Figure 6 shows the optimal solutions from three constrained optimization runs and Table 3 presents a detailed analysis of those optimal designs. In Table 3, 'U-bends L1' and 'U-bends L2' are the number of U-bends which stretches across 1 tube row and 2 tube rows respectively. 'U-bends $\geq$ L3' is the number of long U-bends which stretches more than 2 tube rows.

Case (b) in Table 3 is a loosely constrained optimization run. In this case, manufacturing constraints, i.e. inlets and outlets on the same side, preventing long U-bends and preventing partial overlap U-bends crossovers, are enforced. Figure 6(c) shows its optimal solution. It results in 13.8% capacity improvement. It has 2 circuits, which makes the refrigerant pressure drop more than 12 times higher than the baseline. But the circuitry can be readily manufactured.

Case (c) in Table 3 is another constrained optimization run, in which only refrigerant pressure drop constraint is applied. This constraint restricts the designs to have equal or less refrigerant pressure drop than the baseline. Figure 6(d) shows its optimal solution. It also has 4 circuits as the baseline, a 4% increase of capacity is obtained, and meanwhile refrigerant pressure drop is slightly lower than the baseline. It is worthwhile to mention that other methods in the literature (Domanski *et al.*, 2004; Wu *et al.*, 2008b; Ploskas *et al.*, 2017) have not demonstrated pressure drop constraints, although various mfg. constraints were investigated.

Case (d) in Table 3 is a highly constrained optimization run, in which manufacturing constraints and the pressure drop constraint are applied. Figure 6(e) shows its optimal solution. The optimal design achieves 2.4% capacity increase with desirable low pressure drop. The circuitry has good manufacturability without any long U-bends or U-bend crossovers. Compared with other cases, the optimal solution from case (d) has desired thermal, hydraulic and manufacturability performance. Overall, Table 3 shows that the capacity improvement decreases when adding

constraints. The optimal evaporators in case (c) and (d) provide similar amount of latent cooling as baseline, since all three evaporators have similar sensible heat ratio (SHR).

Table 3: Evaporator Optimization Results with Different Constraints

Case	Baseline	(a)	(b)	(c)	(d)
Constraints	-	No constraints	Mfg. constraints	Refrigerant DP constraint	Mfg. constraints and DP constraint
Capacity [W]	5294	6065(14.6%↑)	6027(13.8%↑)	5497 (3.8%↑)	5421 (2.4%↑)
Ref. DP [kPa]	11.8	972.5 (81x↑)	160.5 (12x↑)	11.4 (3.6%↓)	11.7 (1.0%↓)
SHR	79.6%	67.6%	72.5%	79.8%	80.6%
U-bends L1	82	61	51	17	62
U-bends L2	0	4	35	9	22
U-bends $\geq$ L3	2	2	0	58	0
Collinear U-bends	0	3	0	43	0

Figure 6: Optimal Circuits under Different Constraints (a) Baseline; (b) Unconstrained; (c) With mfg. constraints; (d) With refrigerant DP constraint; (e) With mfg. and refrigerant DP constraints

5. COMPARISON WITH METHODS FROM LITERATURE

Domanski *et al.*(2004) and Wu *et al.*(2008b) once applied their methods to optimize the same 36-tube R22 evaporator as shown in Figure 7(a) under uniform airflow distribution. In this section, the proposed approach is benchmarked against the previous two methods by optimizing the same heat exchanger. To be consistent with the GA settings used by previous researchers, the population size for this optimization run is 15 and number of generation is 200. The boundary condition to simulate this evaporator is specified evaporator outlet condition. According to Domanski *et al.*(2004), the evaporator outlet pressure is fixed at a saturation pressure corresponding to 7.2°C saturation temperature, while the outlet superheat is 5°C. The evaporator inlet enthalpy is determined based on the outlet enthalpy of a condenser, to be specific, the enthalpy at 40°C condensation temperature with 5°C subcooling. The HX structural parameters, operating conditions and correlations are provided in Domanski *et al.*(2004).

Figure 7(b) shows the optimal solution as reported in Domanski *et al.*(2004). It achieves 4.2% capacity increase, accompanied by 27.7% refrigerant pressure drop increase. There is one partial overlap U-bend crossover highlighted in red rectangular and the author suggested to manually modify the circuitry to improve its manufacturability. Figure 7(c) shows optimal solution from Wu *et al.*(2008b). The capacity increase is 4.1%, the manufacturability is better than the former counterpart since there is no long U-bend or partial overlapped collinear U-bends. However, the refrigerant pressure drop also increases by 26.0%. Figure 7(d) shows the optimal solution from the proposed approach. In this optimization run the three manufacturing constraints are applied, besides the pressure drop constraint is relaxed such that 5% increase on refrigerant pressure drop is acceptable. As a result, the capacity improvement is 4.5%. This capacity increase is the largest among all three methods. Although the refrigerant pressure drop increases by 4.7% compared with baseline, it is still lower than the other two optimal designs.

Figure 7: Optimal Solutions: (a) Baseline; (b) Domanski *et al.* (2004); (c) Wu *et al.* (2008b); (d) Proposed approach

6. CONCLUSIONS

A novel integer permutation-based GA approach is presented to solve the tube-fin heat exchanger circuitry optimization problem. Six genetic operators are designed to generate circuitry with potentially better performance. The manufacturability aspect is handled using an efficient constraint-dominated sorting method. The case studies on an experimental validated evaporator show that the proposed optimization approach can generate circuitry designs with capacities superior to circuitries designed manually, while guarantee good manufacturability. Overall, 2.4-14.6% capacity increase is observed with different constraints. Comparison with other optimization methods in literature shows that the proposed approach can find designs which are better than optimal designs obtained from other methods.

7. REFERENCES

- Alabdulkarem, A., Eldeeb, R., Hwang, Y., Aute, V., & Rademacher, R. (2015). Testing, simulation and soft-optimization of R410A low-GWP alternatives in heat pump system. *International Journal of Refrigeration*, 60, 106-117.
- Arora, J. (2004). *Introduction to optimum design*. Elsevier.
- Bahman, A. M., & Groll, E. A. (2017). Application of interleaved circuitry to improve evaporator effectiveness and COP of a packaged AC system. *International Journal of Refrigeration*, 79 (Supplement C), 114-129.
- Bigot, G., Palandre, L., & Clodic, D. (2000). Optimized Design of Heat Exchangers for "Reversible" Heat Pump Using R-407C. The 8th International Refrigeration and Air Conditioning Conference, Purdue
- Blasius, H. (1907). *Grenzschichten in Flüssigkeiten mit kleiner Reibung*: Druck von BG Teubner.
- Cho, H., & Domanski, P. A. (2016). Optimized air-to-refrigerant heat exchanger with low-GWP refrigerants. In *12th Iir Gustav Lorentzen Natural Working Fluids Conference* (pp. 861-868).
- Chwalowski, M., Didion, D., & Domanski, P. (1989). Verification of evaporator computer models and analysis of performance of an evaporator coil. *ASHRAE transactions*, 95, 1229-1236.
- Coit, D. W., & Smith, A. E. (1996). Penalty guided genetic search for reliability design optimization. *Computers & industrial engineering*, 30(4), 895-904.
- Deb, K. (2000). An efficient constraint handling method for genetic algorithms. *Computer Methods in Applied Mechanics and Engineering*, 186(2), 311-338.
- Deb, K. (2012). *Optimization for engineering design: Algorithms and examples*: PHI Learning Pvt. Ltd.
- Dittus, F., & Boelter, L. (1985). Heat transfer in automobile radiators of the tubular type. *International Communications in Heat and Mass Transfer*, 12(1), 3-22.

- Domanski, P. A., & Yashar, D. (2007). Optimization of finned-tube condensers using an intelligent system. *International Journal of Refrigeration*, 30(3), 482-488.
- Domanski, P. A., Yashar, D., Kaufman, K. A., & Michalski, R. S. (2004). An optimized design of finned-tube evaporators using the learnable evolution model. *HVAC&R Research*, 10(2), 201-211.
- Domanski, P. A., Yashar, D., & Kim, M. (2005). Performance of a finned-tube evaporator optimized for different refrigerants and its effect on system efficiency. *International Journal of Refrigeration*, 28(6), 820-827.
- Domanski, P. A., Yashar, D., Lee, S., & Wojtusiak, J. (2011). Practical aspects of applying evolutionary algorithms for optimizing refrigerant circuitry in heat exchangers. The 23rd IIR Int. Congress of Refrigeration, Prague.
- Gen, M., Cheng, R., & Lin, L. (2008). Network models and optimization: Multi-objective genetic algorithm approach. Springer Science & Business Media.
- Goldberg, D. E. (1989). Genetic algorithms in search, optimization, and machine learning. *New York, Addison-Wesley*.
- Goldberg, D. E., & Deb, K. (1991). A comparative analysis of selection schemes used in genetic algorithms. In *Foundations of genetic algorithms* (Vol. 1, pp. 69-93): Elsevier.
- Gray, P., Hart, W., Panton, L., Phillips, C., Trahan, M., & Wagner, J. (1997). A survey of global optimization methods. Sandia National Laboratories, Albuquerque, USA.
- Holland, J. H. (1992). Adaptation in natural and artificial systems: an introductory analysis with applications to biology, control, and artificial intelligence. MIT press.
- Huang, L., Aute, V., & Radermacher, R. (2015). A Survey of Optimization Formulations and Techniques for the Design of Heat Exchangers Using Lower GWP Refrigerants. *ASHRAE Transactions*, 121(CH-15-C039).
- Jiang, H., Aute, V., & Radermacher, R. (2006). CoilDesigner: a general-purpose simulation and design tool for air-to-refrigerant heat exchangers. *International Journal of Refrigeration*, 29(4), 601-610.
- Jung, D., McLinden, M., Radermacher, R., & Didion, D. (1989). A study of flow boiling heat transfer with refrigerant mixtures. *International Journal of Heat and Mass Transfer*, 32(9), 1751-1764.
- Jung, D., & Radermacher, R. (1989). Prediction of pressure drop during horizontal annular flow boiling of pure and mixed refrigerants. *International Journal of Heat and Mass Transfer*, 32(12), 2435-2446.
- Kargupta, H., Deb, K., & Goldberg, D. E. (1992). *Ordering Genetic Algorithms and Deception*. PPSN.
- Lee, W. J., Kim, H. J., & Jeong, J. H. (2016). Method for determining the optimum number of circuits for a fin-tube condenser in a heat pump. *International Journal of Heat and Mass Transfer*, 98, 462-471.
- Li, Z., Ling, J., & Aute, V. (2018). *Tube-Fin Heat Exchanger Circuitry Optimization for Multiple Airflow Maldistribution Profiles*. The 17th International Refrigeration and Air Conditioning Conference, Purdue.
- Liang, S., Wong, T., & Nathan, G. (2000). Study on refrigerant circuitry of condenser coils with exergy destruction analysis. *Applied Thermal Engineering*, 20(6), 559-577.
- Liang, S., Wong, T., & Nathan, G. (2001). Numerical and experimental studies of refrigerant circuitry of evaporator coils. *International Journal of Refrigeration*, 24(8), 823-833.
- Ploskas, N., Laughman, C., Raghunathan, A. U., & Sahinidis, N. V. (2017). Optimization of circuitry arrangements for heat exchangers using derivative-free optimization. *Chemical Engineering Research and Design*.
- Spears, W. M., & Jong, K. A. (1998). *The role of mutation and recombination in evolutionary algorithms*. (PhD Thesis), George Mason University, Fairfax, VA.
- Wang, C.-C., Jang, J.-Y., Lai, C.-C., & Chang, Y.-J. (1999). Effect of circuit arrangement on the performance of air-cooled condensers. *International Journal of Refrigeration*, 22(4), 275-282.
- Wang, C.-C., Tsai, Y.-M., & Lu, D.-C. (1998). Comprehensive study of convex-louver and wavy fin-and-tube heat exchangers. *Journal of Thermophysics and Heat transfer*, 12(3), 423-430.
- Wu, Z., Ding, G., Wang, K., & Fukaya, M. (2008a). Application of a genetic algorithm to optimize the refrigerant circuit of fin-and-tube heat exchangers for maximum heat transfer or shortest tube. *International Journal of Thermal Sciences*, 47(8), 985-997.
- Wu, Z., Ding, G., Wang, K., & Fukaya, M. (2008b). Knowledge-Based Evolution Method for Optimizing Refrigerant Circuitry of Fin-and-Tube Heat Exchangers. *HVAC&R Research*, 14(3), 435-452.
- Yashar, D., Wojtusiak, J., Kaufman, K. A., & Domanski, P. A. (2010). Evolutionary Computation Approach to Heat Exchanger Design. In *Ashrae Transactions 2010, Vol 116, Pt 2* (Vol. 116, pp. 135-142).
- Yashar, D. A., Lee, S., & Domanski, P. A. (2015). Rooftop air-conditioning unit performance improvement using refrigerant circuitry optimization. *Applied Thermal Engineering*, 83, 81-87.
- Yashar, D. A., Wojtusiak, J., Kaufman, K., & Domanski, P. A. (2012). A dual-mode evolutionary algorithm for designing optimized refrigerant circuitries for finned-tube heat exchangers. *HVAC&R Research*, 18(5), 834-844.