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A novel single and multi-objective optimization approach based on Bees Algorithm Hybrid with Particle Swarm Optimization (BAHPSO): Application to thermal-economic design of plate fin heat exchangers

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ABSTRACT

As a novel hybrid optimization approach, the single and multi-objective BAHPSO are investigated for thermal designing of the cross-flow plate fin heat exchanger (PFHE) under given heat duty and pressure drop constraints. Because both of the Particle Swarm Optimization (PSO) and Bess Algorithm (BA) are operating with a random primary population of solutions, the current study combined their searching abilities for the first time, and presented a novel searching procedure named BAHPSO. In the current investigation, Multi-Objective optimization (MO) of BAHPSO is simultaneously employed to acquire the maximum effectiveness and the minimum total annual cost (TAC) of a heat exchanger as two contradict objectives and then results are compared with MOPSO and MOBA. Hot and cold side length, fin frequency, number of fin layers, fin thickness, fin height, and fin lance length are chosen as seven decision parameters. Also, a sensitivity analysis is performed to study the impact of geometrical parameters on each objective function. Finally, accuracy and efficiency of the presented algorithm is proven via illustrative single-objective optimization case studies which adopted from the references. Results demonstrate that the BAHPSO can detect optimal shape with higher accuracy compared to other algorithms.

1. Introduction

Compact heat exchanger (CHE) is one of the most significant kinds of industrial heat exchangers (HEs). The key feature of CHEs is their large heat exchange surface area per unit volume and can be manufactured in both types of tube-fin and PFHE [1]. High effectiveness, compact size, light weight and multi-current capability are the notable advantages lead to the vast use of PFHEs in the gas to gas applications, including: helium and oxygen liquefaction plants, aerospace, air separation plants, micro-turbines, transport industries such as motor and aircraft engines, cryogenic, petroleum, and chemical industries [2].

Fins (extended surfaces) are the main factors decline the size and enhance the heat transfer in CHEs [3,4]. Some common types of fins used in such exchangers are plain fin strip, louvered fin, perforated fin, pin and wavy fins [5]. PFHE is designed in a sophisticated process of trial-and-error where geometric and operational variables are defined to fulfill determined requirements namely outlet temperature, pressure drop and heat duty. Many works have exclusively addressed HEs optimization through traditional mathematical methods [6–10]. The design of HEs by evolutionary algorithms has been recently paid special attention. Computational optimization has been an active research area for many decades. Swarm-based optimization algorithms (SOAs) imitate nature's methods to find a way towards the optimum solution. A newfound research field, the swarm intelligence presents characteristics of self-organization and collaboration principles among group members who are bio-inspired on social insect societies. Actually, optimization techniques are being widely utilized in different aspects of human activities, where some complicated situation that can be stated in a mathematical model makes human beings take a decision. Several optimization algorithms have been designed according to the nature inspired analogy in the past few decades. These are frequently metaheuristics based on population, and they are also named general

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Nomenclature

A	heat exchanger surface area (m^2)
A_{ff}	free flow area (m^2)
C	heat capacity rate (W/K)
C	cost ($)
C_p	specific heat (J/kg K)
C_r	C_{min}/C_{max}
c_1,c_2	acceleration parameter (for PSO algorithm)
D_h	hydraulic diameter (m)
f	fanning friction factor
$f(x)$	objective function
$g(x)$	constrain function
G	mass flux velocity (kg/m^2s)
h	convective heat transfer coefficient (W/m^2K)
H	height of fin (m)
j	Colburn factor
l	lance length of the fin (m)
L	heat exchanger length (m)
m	mass flow rate (kg/s)
n	fin frequency (fin/m)
N_a	number of fin layers for fluid *a*
N_b	number of fin layers for fluid *b*
N_s	number of entropy generation units (NEGUs)
NTU	number of transfer units
P	pressure (N/m^2)
Pr	Prandtl number
Q	heat duty (W)
R	specific gas constant (J/kg K)
Re	Reynolds number
s	fin spacing (m)
$\dot{S}$	rate of entropy generation (W/K)
t	fin thickness (m)
T	temperature (K)
U	overall heat transfer coefficient (W/m^2K)
v	particle velocity (for PSO algorithm)
w	inertia weight (for PSO algorithm)

Greek symbols

ε	effectiveness
μ	viscosity (Pa s)
ρ	density (kg/m^3)
ΔP	pressure drop (Pa)
ΔS	entropy difference (W/kg K)

Subscripts

a, b	fluid *a* and *b*
tot	total
1	Inlet
2	Outlet
max	Maximum
min	Minimum

objective algorithms due to their usage to a great range of case studies. Genetic algorithms (GA) [11,12], PSO [13], BA [14], Differential Evolution (DE) [15], Evolutionary Programming (EP) [16], Ant Colony Optimization (ACO) [17], etc. are among the popular optimization algorithms.

For a non-trivial MO problem, there is not just one solution which optimizes each of the objectives, simultaneously. In such cases, the objective functions (OFs) are called to be contradicting, and there are many Pareto optimal solutions. For PFHEs, the researchers successfully employed MO using GA to gain a set of geometric design variables to get two contradicting OFs, including total heat exchange rate, number of entropy generation units (NEGUs), TAC, and effectiveness [2,18,19]. Rao et al. [20] utilized a TLBO algorithm for achieving maximum effectiveness and minimum TAC as two distinct OFs in two types of HEs. Ahmadi et al. [21] minimized the NEGUs as well as the TAC in a PFHE constructed by offset-strip-fins. Yousefi et al. [22] employed a swarm intelligent procedure for MO of compact HEs. Results reflect the better performance of the presented algorithm compared to the conventional non-dominated sorting GA II. Very recently, new and/or hybrid algorithms such as IMOCS [23], MO-ITLBO [24], BBO [25] and MOFSDE [26] applied to MO of PFHEs. In state of single-objective optimization, Mishra et al. [27] optimized a PFHE according to the second law of thermodynamics in order to minimize the NEGUs for specific heat duty. Also, Xie et al. [28] employed GA to optimize a CHE under pressure drop restrictions. PSO algorithm is applied for the sake of a PFHE optimization by Rao and Patel [29]. On the other hand, by using ICA, Yousefi et al. [30,32] optimized a cross-flow PFHE to minimize NEGUs, TAC, and weight under given restrictions. Results indicated the better efficiency of ICA and Learning Automata based Particle Swarm Optimization (LAPSO) compared to the traditional GA and PSO. Hadidi et al. [25] proposed the BBO algorithm to optimize the design of PFHEs. Recently, Turgut [33] employed a HCQPSO algorithm to optimize a PFHE in order to minimize TAC, pressure drop, and heat exchange area under given limitations. Their numerical results showed that this approach is able to generate optimum solutions of higher accuracy in comparison to Improved Harmony Search (IHS) algorithm, ICA, and GAHPSO.

There exist also other SOAs whose names suggest possibly bee-inspired operations [34–37]. Nevertheless, to the author's best knowledge, such algorithms do not closely mimic bees' behavior. More importantly, they do not appear to employ the same strategies as those bees implement while foraging for food. Thus, Pham et al. [38] studied the first use of the BA to obtain the optimum design for mechanical problems. They investigated two standard case studies: helical spring and welded beams designing. The purpose of that investigation was to examine the efficiency of the BA in comparison with the other optimization algorithms. Results proved the excellence of BA compared to the others. Also, Zarea et al. [39–42] successfully utilized a BA for optimization of a cross-flow PFHE. Though, in spite of several attractive features, the observations suggested that these algorithms do not always perform as expected. A careful balance between two contradicting objectives, exploration (diversification) and exploitation (intensification), to a large extent, determines the achievement of most of the metaheuristics optimization algorithms. Exploration is necessary to ensure that an adequate search in each part of the solution domain is performed to provide a trustworthy approximate of the global optimum. However, the exploitation importance is due to focus the search attempt on the best solutions found till now by exploring their neighborhoods to achieve better solutions [43]. Search algorithms are able to reach these two aims by employing local and global search methods, or a hybrid of them. These algorithms are mostly called hybrid methods. Van den Bergh [44] showed that PSO does not guarantee the convergence to the global optimum. Specifically, when the dimensions of the objective functions are high and multiple local optima exist simultaneously, PSO simply falls into local optima results in a low optimizing precision or even failure. In this situation, the optimizing performance will not be easily enhanced by merely enlarging the population size or enhancing the evolution run-times.

Researchers have improved PSO efficiency by utilizing fundamentals of other well-known methods, for example selection, mutation and crossover of GA and also DE in it. Efforts have also been made to enhance the efficacy of other evolutionary algorithms including; GA, DE, ACO, and etc. by incorporating velocity and position update