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Design of shell-and-tube heat exchangers using multiobjective optimization

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ABSTRACT

In this paper, a multiobjective optimization of the heat transfer area and pumping power of a shell-and-tube heat exchanger is presented to provide the designer with multiple Pareto-optimal solutions which capture the trade-off between the two objectives. Nine decision variables were considered: tube layout pattern, number of tube passes, baffle spacing, baffle cut, tube-to-baffle diametrical clearance, shell-to-baffle diametrical clearance, tube length, tube outer diameter, and tube wall thickness. The optimization was performed using the fast and elitist non-dominated sorting genetic algorithm (NSGA-II) available in the multiobjective genetic algorithm module of MATLAB®. In order to verify the improvements in design that the method offers, two case studies from the open literature are presented. The results show that for both case studies, better values of the two objective functions can be obtained than the ones previously published. In addition, NSGA-II provides a Pareto front with a wider range of optimal decision variables. Ranking the Pareto-optimal solutions using a simple cost function shows that the costs for optimal design are lower than those reported in the literature for both case studies. The algorithm was also used to determine the impact of using continuous values of the tube length, diameter and thickness rather than using discrete standard industrial values to obtain the optimal heat transfer area and pumping power. Results show that using continuous values of these three decision variables only leads to marginally improved performance compared to discrete values.

1. Introduction

Heat exchangers are ubiquitous pieces of equipment in the process industry. Several types and designs of heat exchangers are used in industrial processes. These include double pipe heat exchangers, shell-and-tube exchangers, plate-and-frame exchangers and many others. However, the more common type of heat exchangers is by far the shell-and-tube heat exchanger. Significant effort has been devoted in recent decades to improve their efficiency in order to conserve energy and render processes more profitable. As energy continues to become more expensive with decreasing fossil fuel resources, optimal design and operation of heat exchangers are required. Improvements in heat exchanger design can have significant advantages such as decreasing the amount of external utilities used which would reduce operating costs and increase profits, in addition to lowering the environmental footprint of the process.

Many handbooks covering the design of shell-and-tube heat exchangers are available. These include the compilation edited by Schlunder [1], Hewitt [2], Saunders [3], and Shah and Sekulic [4]. These references are recommended as a good source of information on heat exchanger design, especially for shell-and-tube heat exchangers.

The design method of segmented baffle shell-and-tube heat exchangers involves an iterative algorithm where several configurations are tested by trial and error until the convergence of the heat transfer coefficient and the tube and shell-side pressure drops are within the maximum allowable values. However, this method often results in oversized equipment without being guaranteed to be optimal [5].

Over the last years, genetic algorithms (GAs) have received a lot of attention as an optimization method in heat transfer and shell-and-tube heat exchanger design in particular. GAs mimic nature's evolutionary process to find an optimal solution. A recent review on the application of GAs in heat transfer reported interesting optimization studies on the design of heat exchangers [6]. Optimization algorithms can be divided into two categories. The first category, known as single objective optimization, consists of finding the global minimum or maximum of an aggregating function normally composed of the weighted sum of the individual objectives. The second category is multiobjective optimization, which involves the simultaneous optimization of multiple, often conflicting, objectives. Instead of finding a unique optimal solution, a set of optimal non-dominated solutions is generated; this set is referred to as the Pareto domain. A solution (A) is said to dominate a solution (B) when (A) is not worse than (B) in any of its objective

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Nomenclature

A_o	heat transfer surface area (m^2)
$A_{o,cr}$	flow area at or near the shell centerline for one cross-flow section (m^2)
$A_{o,sb}$	shell-to-baffle leakage flow area (m^2)
$A_{o,tb}$	tube-to-shell leakage flow area (m^2)
B	bare module factor
B_c	baffle cut (%)
C	purchase cost coefficient
C_{BM}	bare module cost
c_p	heat capacity (J kg^{-1} K)
C_p	purchase cost of the exchanger ($)
d_i	tube inside diameter (m)
d_o	tube outside diameter (m)
D_{otl}	tube bundle outer diameter (m)
D_s	shell diameter (m)
ec	electricity cost ($kW^{-1} h)
F	correction factor for the number of tube passes
F_M	material correction factor
G	fluid mass velocity (kg m^2 s)
h	heat transfer coefficient (W m^{-2} K)
i	interest rate (%)
I	cost index
J	correction factor for the shell-side heat transfer
k	thermal conductivity (W m^{-2} K)
K	capital cost correlation factor
L_b	distance between baffles (m)
$\dot{m}$	mass flow rate (kg s^{-1})
n	lifetime of the exchanger (year)
N_b	number of baffles
N_p	number of tube passes
N_{ss}	number of sealing strip pairs
N_t	total number of tubes
OC	operating cost ($ year^{-1})
op	annual operating period (h)
Pr	Prandtl number
P_t	tube pitch (m)
$P_{s,t}$	Pumping power on tube and shell sides (W)
Q	heat duty (W)
R	fouling resistance (m^2 kW^{-1})
Re	Reynolds number
t	tube thickness (m)
T	temperature (°C)
TC	annualized cost of the heat exchanger ($ year^{-1})
U_o	overall heat transfer coefficient (W m^{-2} K)
v	flow velocity (m s^{-1})

Greek symbols

ζ	shell-side pressure drop correction factor
μ	viscosity (Pa s)
δ	density (kg m^{-3})
ΔP	pressure drop
ΔT_{lm}	log-mean temperature difference

Subscript

c	cold fluid, center of the exchanger
h	hot fluid
i	tube inlet
id	ideal
M	material
o	tube outlet
P	pressure
s	shell-side
t	tube-side
w	tube wall

function values and it is better with respect to at least one objective [7].

A number of earlier optimization studies using GAs only considered a single objective. Selbas et al. used a binary-coded GA to minimize a cost function [8]. Their decision variables were the tube diameter, tube pitch, number of passes, shell outer diameter and baffle cut. Wildi-Tremblay and Gosselin performed an optimization study on a heat exchanger with a given heat duty by minimizing a cost function [9]. A binary-coded GA was employed to carry the optimization with 11 discrete decision variables: the tube pitch, tube layout pattern, number of tube passes, baffle spacing at the center, baffle spacing at the inlet and outlet, baffle cut, tube-to-baffle diametrical clearance, shell-to-baffle diametrical clearance, tube bundle outer diameter, shell diameter and tube outer diameter. Results indicated that the GA identified the optimal results much faster than evaluating all possible combinations of decision variables.

Later Allen and Gosselin expanded this optimization work to consider a condenser shell-and-tube heat exchanger, using the identical cost function [10]. The decision variables were augmented by one to include the heat exchanger side where condensation occurs (shell or tube side).

Babu and Munawar used differential evolution (DE) optimization for the design of a heat exchanger [11]. They chose the minimization of a cost function as their objective and seven decision variables: the tube outer diameter, tube pitch, shell type, number of tube passes, tube length, baffle spacing and baffle cut.

Ozcelik used GA to minimize the exergetic cost of a heat exchanger with the following decision variables: tube length, outer tube diameter, pitch type, pitch ratio, tube layout angle, number of tube passes, baffle spacing ratio, and the mass flowrate of the utility [12].

Caputo et al. employed the MATLAB® genetic alogorithm toolbox to minimize the cost of a shell-and-tube heat exchanger [13]. They chose a cost function which was the sum of the capital investment and the discounted annual energy for pumping as their objective and used three decision variables: shell diameter, tube diameter, and baffle spacing. Their results indicated a reduction in cost when compared to exchangers designed using traditional methods [13].

Hajabdollahi et al. [14] have performed a thermo-economic optimization of a shell-and-tube condenser. They employed both genetic algorithm and particle swarm algorithms to minimize a cost function which included the investment and operating cost of the condenser. The decision variables were the number of tubes, number of tube passes, inlet and outlet tube diameters, tube pitch ratio and tube layout. Results indicated that the optimal shell diameter was less than 7 m and the optimal tube length less than 15 m, the ratio of diameter to tube length varied between 1/12 to 1/3, and GA had a lower CPU time compared to particle swarm.

Although single-objective optimization has been often used in the literature, this method does not provide any information about the trade-off between various competing objectives and may converge on a local instead of a global optimum in complex problems. Furthermore the results obtained by using single-objective