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Automated heat exchanger network synthesis by using hybrid natural algorithms and parallel processing

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ABSTRACT

Heat exchanger network (HEN) synthesis can be formulated as an optimization problem, which can be solved by meta-heuristics. These approaches account for a large computational time until convergence. In the present paper the potentialities of applying parallel processing techniques to a non-deterministic approach based on a hybridization between Genetic Algorithms (GA) and Particle Swarm Optimization (PSO) were investigated. Six literature examples were used as benchmarks for the solutions obtained. Comparative experiments were carried out to investigate the time efficiency of the method while implemented using series or parallel processing. The solutions obtained led to lower Total Annual Costs (TAC) than those presented by the literature. As expected, parallel processing usage multiplied the algorithm speed by the number of cores used. Hence, it can be concluded that the proposed method is capable of finding excellent local optimal solutions, and the application of multiprocessing techniques represented a substantial reduction in execution time.

1. Introduction

Few areas of study in industrial processes are capable of generating actual capital savings of magnitude comparable to those originated from heat integration. Large share of this field is bound purely to Heat exchanger network synthesis (HEN). The heat recovered from the process streams through the HEN yields important savings in utilities used to heat or cool process fluids. Moreover, it is necessary to underline that the energy integration of a plant culminates directly in a significant reduction on the emissions of greenhouse gases. For these reasons, obtaining optimal HEN configurations in an industrial plant is a valuable and widely studied subject. Methods to obtain solutions to the HEN synthesis problem can be essentially based on sequential heuristics or mathematical programming, which require deterministic or non-deterministic approaches in order to achieve optimal solutions. Moreover, a challenging feature that is also considered in this work is the presence of process streams with phase change, which requires some extra constraints to be used and makes HEN synthesis problems even more difficult.

While demonstrating efficiency in obtaining optimal or near-optimal solutions, stochastic methods require the execution of massive quantities of computational operations. Hence, these techniques may lead to rather high processing times. This is due to the fact that most of these methods employ populations of candidate solutions and are guided by the best solutions found at each iteration.

Computers with multi-core processors have become rather common and affordable. With this technology, calculations can be performed in parallel by using two or more processor cores in order to save time. In this research, an attempt to aggregate the potential of two known non-deterministic optimization methods is aimed, while investigating the performance improvement provided by multiprocessing techniques. A hybridization method using Genetic Algorithms and Particle Swarm Optimization was developed. It gives the possibility of significant part of the calculations to be performed in parallel. In addition, improved forms of both methods are implemented in order to improve the quality of the solutions by balancing local minima avoidance through diversity of solutions and processing time. Hence, in this work, not only solutions quality but time efficiency improvements are investigated.

1.1. Literature review

Literature has presented numerous approaches in order to achieve optimal heat exchangers combination, which minimizes deployment costs along with hot and cold utilities costs. At first, the methodologies were based primarily on heuristics and

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Nomenclature

Methodologies (Genetic Algorithm)

C1 Lower TAC in the generation
Cn Higher TAC in the generation
couples Number of crossovers per generation
CrossProb Crossover probability
Ctotal Total annual costs
elim Number of eliminated individuals after crossover
fitness Fitness of an individual
genmax Maximum number of generations
mutchance Probability of applying mutation schemes
mutchance11 Probability of applying classic mutation
mutchance12 Probability of flipping a binary variable if classic mutation is applied
$mutchance12_{max}$ Maximum probability of flipping a binary variable if classic mutation is applied
$mutchance12_{min}$ Minimum probability of flipping a binary variable if classic mutation is applied
mutchance2 "Match Stage Swap" mutation probability
mutchance3 "Stage Scramble" mutation probability
$mutchance_{max}$ Maximum probability of applying mutation schemes
$mutchance_{min}$ Minimum probability of applying mutation schemes
Pop Initial population
T General variable for mutation probability in Eq. (40).
Tmax Maximum mutation probability in Eq. (40)
Tmin Minimum mutation probability in Eq. (40)

Methodologies (Particle Swarm Optimization)

C1 Lower TAC in the generation
c1 and c2 Parameters related to particle's best and global best positions
closeptmax Maximum number of particles that may be closer than "edistmin" from global best without a reset
Cn Higher TAC in the generation
C_{pen} Penalty constant
E Euclidean distance
edistmin Minimum Euclidean Distance between particles position and global best position
K Total number of iterations (Eq. (44))
Npt Number of particles
p Particle's best position
pen Penalty value
p^{global} Best position found by the swarm
r1 and r2 Random number between 0 and 1
resetmax Maximum number of times the particles velocities can be reset
sameobjmax Maximum iterations allowed when global best position value stagnates before a reset is imposed
totaliteropt Total PSO iterations in optimization stage
$totaliteropt_{max}$ Maximum total PSO iterations in optimization stage
$totaliteropt_{min}$ Minimum total PSO iterations in optimization stage
totaliterpostopt Maximum PSO iterations in post-optimization stage
totaliterpreopt Total PSO iterations in pre-optimization stage
v Particle velocity
ω Inertia weight
ω_{max} Maximum inertia weight
ω_{min} Minimum inertia weight
X Generic variable
x Particle position
X^{Bound} Generic variable lower or upper bound

Subscripts/Indexes

i Particle index
k PSO iteration
x Index of an individual in GA population

Mathematical Modeling (Variables)

A Heat exchanger area [m^2]
Acu Cooler area [m^2]
Ahu Heater area [m^2]
C_{total} Heat exchanger network total annual costs [$/y]
Fc Fraction of a cold stream branch [−]
Fh Fraction of a hot stream branch [−]
LMTD Logarithmic mean temperature difference [K]
$n_{continuous}$ Number of continuous variables [−]
n_F Number of stream split fraction variables [−]
n_Q Number of heat load variables [−]
n_{total} Total number of variables [−]
n_z Number of binary variables [−]
Q Heat load in a heat exchanger [kW]
Q_C Total heat load of cold utilities [kW]
Qcu Heat load in a cooler [kW]
Q_H Total heat load of hot utilities [kW]
Qhu Heat load in a heater [kW]
Qmax Maximum exchangeable heat load in a heat exchanger [kW]
Tchuin Process cold stream inlet temperature in heaters [K]
Tcout Process cold stream outlet temperature from a heat exchanger [K]
Thcuin Process hot stream inlet temperature in coolers [K]
Thout Process hot stream outlet temperature from a heat exchanger [K]
Tmixc Temperature after mixers on cold streams [K]
Tmixh Temperature after mixers on hot streams [K]
U Global heat transfer coefficient [kW/(m^2 K)]
z Binary variable representing existence of a heat exchanger [−]
zcu Binary variable representing existence of a cooler [−]
zhu Binary variable representing existence of a heater [−]
$\theta^{(1)}$ Approach temperature on the hot end of a heat exchanger [K]
$\theta^{(2)}$ Approach temperature on the cold end of a heat exchanger [K]
$\theta^{(3)}$ Difference between cold and hot streams phase change temperatures [K]

Mathematical Modeling (Parameters)

CA Area costs coefficient [$/($m^{2\beta}$y)]
Ccu Cold utility cost [$/(kW y)]
CF Heat exchanger fixed deployment costs [$/y]
Chu Hot utility cost [$/(kW y)]
CP Stream total heat capacity [kW/K]
CPc Cold stream total heat capacity [kW/K]
CPh Hot stream total heat capacity [kW/K]
EMAT Heat Exchanger minimum temperature approach [K]