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Research Paper

A novel hybrid chaotic ant swarm algorithm for heat exchanger networks synthesis

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HIGHLIGHTS

- The chaotic ant swarm algorithm is proposed to avoid trapping into a local optimum.
- The organization variables update strategy makes full use of advantages of the chaotic search.
- The structure evolution strategy is developed to handle integer variables optimization.
- Overall three cases taken form the literatures are investigated with better optima.

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ABSTRACT

The heat exchanger networks synthesis (HENS) still remains an open problem due to its combinatorial nature, which can easily result in suboptimal design and unacceptable calculation effort. In this paper, a novel hybrid chaotic ant swarm algorithm is proposed. The presented algorithm, which consists of a combination of chaotic ant swarm (CAS) algorithm, structure evolution strategy, local optimization strategy and organization variables update strategy, can simultaneously optimize continuous variables and integer variables. The CAS algorithm chaotically searches and generates new solutions in the given space, and subsequently the structure evolution strategy evolves the structures represented by the solutions and limits the search space. Furthermore, the local optimizing strategy and the organization variables update strategy are introduced to enhance the performance of the algorithm. The study of three different cases, found in the literature, revealed special search abilities in both structure space and continuous variable space.

1. Introduction

As an important field in the process systems engineering, the heat exchanger networks synthesis (HENS), which aims to maximize energy recovery or minimize total annual costs (TAC), has been extensively studied over the last 50 years. A large number of papers focusing on distinct synthesis approaches have been published. Two primary approaches have been proposed for HENS, namely, sequential and simultaneous methods [1].

Sequential methods usually decompose the HENS problem into a series of smaller sub-problems with different objectives in order to reduce the computing complexity. The pinch method based on the laws of thermodynamics [2,3], as a sequential method, has a wide range of applications in industrial fields. By sequentially solving different targets consisting of minimum number of units, minimum heat transfer areas and minimum utility consumption, this method has proven effective and applicable to real plant situations [4–6]. However, the sequential nature of these methods limits their ability that accurately trade-off between utility and exchanger costs, leading to suboptimal network designs.

Simultaneous methods are primarily formulated as mixed integer non-linear programming (MINLP) models, which have been widely developed and shown to be superior to sequential approaches in most cases [7,8]. Furman and Sahinidis [9] have analyzed the computational complexity of the HENS, demonstrating that it actually belongs to the class of NP-hard problems. Generally, global optimization approaches based on MINLP models, which are suitable for simultaneous HENS problems, can be broadly divided into deterministic methods and stochastic methods [10]. Deterministic methods, such as outer approximation (OA) [11], branch and reduce algorithm [12], branch and bound technique (BB) [13], have been used to solve HENS problems. The solution strategies based on stochastic algorithms often have a bi-level structure.

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Nomenclature

Variables

a, b, c	positive constants
d	distance between ants
h	individual heat transfer coefficient for streams (kW/m^2/K)
r	organization factor
y	organization variable
$A_{HU,j}$	area of heaters (m^2)
$A_{CU,i}$	area of coolers (m^2)
$A_{i,j,k}$	area of heat exchangers (m^2)
$B_{HU,j}$	0–1 binary variables representing the existence of heaters
$B_{CU,i}$	0–1 binary variables representing the existence of coolers
$B_{i,j,k}$	0–1 binary variables representing the existence of heat exchangers
C_{HU}	utility cost coefficient of hot utility
C_{CU}	utility cost coefficient of cold utility
C_{HF}	fixed charge of heaters
C_{CF}	fixed charge of coolers
C_{EF}	fixed charge of heat exchangers
C_{HE}	area cost coefficient of heaters
C_{CE}	area cost coefficient of coolers
C_{EE}	area cost coefficient of heat exchangers
I	given iterative step
J	given iterative step
K	time index of iteration
M	penalty coefficient
N	number of existing heat exchangers
N_C	number of cold streams
N_H	number of heat streams
N_P	population size
N_S	number of stages
N_g	number of the generated heat exchangers
N_e	number of the eliminated heat exchangers
N_{EX}^i	number of heat exchangers in the hot stream i
N_{EX}^j	number of heat exchangers in the cold stream j
N_z	number of the thermodynamic constraints
N_b	index of a heat exchanger
$N_{c,\max}$	maximum number of heat exchangers in cold streams
$N_{h,\max}$	maximum number of heat exchangers in hot streams
P	probability
$Q_{i,j,k}$	heat load of heat exchangers (kW)
$Q_{HU,j}$	heat load of hot utility for the cold stream j (kW)
$Q_{CU,i}$	heat load of cold utility for the hot stream i (kW)
$Q_{\min}$	minimum heat load of heat exchangers (kW)
$Q_{\max}$	maximum heat load of heat exchangers (kW)
$T_{h,i,k}^{in}$	inlet temperatures of a single heat exchanger at hot stream i (K) or (°C)
$T_{h,i,k}^{out}$	outlet temperatures of a single heat exchanger at hot stream i (K) or (°C)
$T_{c,j,k}^{in}$	inlet temperatures of the same heat exchanger at cold stream j (K) or (°C)
$T_{c,j,k}^{out}$	outlet temperatures of the same heat exchanger at cold stream j (K) or (°C)
T_i^{in}	supply temperatures of the hot stream i (K) or (°C)
T_i^{out}	target temperatures of the hot stream i (K) or (°C)
T_j^{in}	supply temperatures of the cold stream j (K) or (°C)
T_j^{out}	the target temperatures of the cold stream j (K) or (°C)
$\Delta T_{\min}$	minimum heat exchange temperature difference (K) or (°C)
ΔT_z	temperature difference of the thermodynamic constraints. (K) or (°C)
U	overall heat transfer coefficient (kW/m^2/K)
W_i	heat capacity flow rate of the hot stream i (kW/K)
W_j	heat capacity flow rate of the cold stream j (kW/K)
Z	exponent for area cost
ε	solution precision
λ	search length of one dimensional search
θ	heat exchange temperature difference of inlet and outlet
$rand$	uniform random number in the range [0,1]

For instance, Athier et al. [14] used a sequential quadratic programming (SQP) to optimize the continuous variables for given structures generated with a simulated annealing algorithm. Lewin et al. [15] used a genetic algorithm (GA) to search the optimal structure of the HEN and subsequently applied the Simplex algorithm to determine the continuous variables. Huo et al. [16] also presented a bi-level approach, in which the GA operators manipulate the structure optimization, while the low level handles the continuous variables with a particle swarm optimization (PSO) algorithm. Luo et al. [17] developed a hybrid genetic algorithm for the optimal design of a HEN, in which the structure and process parameters were optimized by different methods, and introducing strategies to keep the diversification in a population and successfully determine continuous variables. Peng and Cui [18], Dipama et al. [19], Silva et al. [20] also presented simultaneous bi-level synthesis methods, in which the upper and the lower level were determined by the same method, i.e. the simulated annealing algorithm (SA), GA and PSO respectively.

Despite its substantial achievements, the bi-level methodology in HENS is still suffering from serious problems. Since the quality of the optimization of process parameters in the lower level directly determines the survival life of the corresponding structure in the upper level, and the total annual cost strongly depends on the network structure, the effectiveness of bi-level methodologies will be greatly weakened if either algorithm cannot handle the corresponding variables successfully. Consequently, even for a middle-scale HENS problem, the number of structures may become prohibitively large, leading to an unmanageable size. In other words, it is almost impossible for stochastic algorithms to find a global optimum especially for large HENS problems. Thus, a more efficient and superior approach for the simultaneous synthesis of heat exchanger network problems should be proposed, which is the aim of this work.

Recently, chaotic optimization algorithms have attracted the attention of many researchers. Some algorithms [21–25] based on chaotic dynamics have been designed in order to solve the optimization problems. Since chaotic variables can go through every state non-repeatedly in a certain region according to its ergodicity, chaotic optimization algorithms have nice capabilities of hill-climbing and escaping from local optima, which indicates that the chaotic search is more effective than the random search [26]. The chaotic ant swarm (CAS) algorithm based on the chaotic behavior of the single ant and the intelligent organization actions of the ant colony is essentially a chaotic optimization algorithm [27], which has been successfully applied to the optimization of process systems [28–30]. Hence, in this work, the CAS algorithm is applied to overcome drawbacks of stochastic algorithms. Furthermore, the structure evolution strategy, the local optimizing