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System Optimization Strategy Based on Genetic Algorithm and Controlled Random Search

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Abstract: A new strategy is proposed for system optimization which is based on the genetic algorithm and the controlled random search. At the top level, the genetic algorithm is used for system structure optimization, while at the bottom level, the controlled random search is used for parameter optimization for the candidate structures provided by the top level, whose results are returned to the top level as the basis for evaluating their corresponding structures. The method can be used to deal with large-scale system optimization problems, and the local optimum problem can be avoided more efficiently. Its effectiveness is demonstrated by applying it to a typical heat exchanger network optimization.

Key words: system optimization; genetic algorithm; controlled random search; heat exchanger network optimization
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基于遗传算法和受控随机搜索的系统优化策略

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摘要:提出一种基于遗传算法和受控随机搜索的系统优化策略.在顶层用遗传算法对系统结构进行优化,在底层,用受控随机搜索对顶层提供的候选结构进行参数优化,并将结果返回给顶层作为遗传算法对相应结构的评判依据.该方法可用于解决较大规模的系统优化问题,并能很好地避免局部最优.通过典型换热网络优化的例子,验证了该方法的有效性.最后,给出了结论.

关键词:系统优化;遗传算法;受控随机搜索;换热网络优化

1 Introduction

The optimal system design consists of two parts, namely structure optimization and parameter optimization. Generally speaking, the structure of a system determines its possible performance, while a structure is usually evaluated by carrying out its parameter optimization according to a specific objective function. As the complexity of a system and the number of its components increase, it is very difficult to find a reasonably optimal structure. In a sense, this is a problem called combinatorial explosion. For example, in a heat exchanger network which is composed of many hot and cold streams, the number of possible structures increases enormously as the number of hot and cold streams increase, thus making it rather difficult to obtain an optimal structure from those possible structures. Many system optimization problems exist in structure and its parameterization, most of which can be cast into a mixed integer nonlinear programming problem. In this paper, a new strategy is proposed for solving these problems.

2 Two-level system optimization strategy

The basic idea proposed here is to use genetic algorithms for structural optimization for those systems which exhibit the property of combinatorial explosion. The fitness function used in the genetic algorithm is obtained by calling a parameter optimization algorithm, the controlled random search. Specifically, the two-level optimization strategy is adopted: at the top level, the genetic algorithm is used and the genetic operators are applied on the structure samples to generate a new generation of samples of system structures; while at the bottom level, the controlled random search is employed to conduct parameter optimization for the candidate system structure assigned by the top level, and its results are returned to

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the genetic algorithm at the top level as the values of fitness of corresponding system structures. The logical structure of the algorithm is shown in Fig. 1.

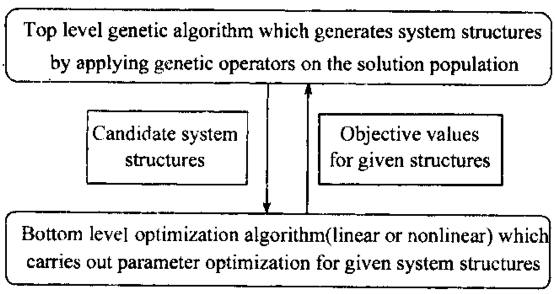

Fig. 1 Logical structure ofthe algorithm

The genetic algorithm (GA) is a kind of globally convergent algorithms, however, substantially it conducts unconstrained optimization[1]. So far, the GA can only be used to deal with simple constrained problems. For constrained optimization problems, the common practice is to use penalty function method; namely, to transform constrained problems into unconstrained ones, then GA is used to solve the latter problems. However, in doing so, the penalty functions are not easy to determine and their forms are dependent on specific problems. Even when the form of a penalty function is found, it is also difficult to select parameters properly.

In the algorthm presented in this paper, the feasibility of a system structure is not considered in the top-level's genetic algorithm, in other words, the genetic algorithm just deals with structure optimization problem which is unconstrained. To be more specific, the top-level's genetic algorithm transfers this task to the bottom-level's controlled random search: for those system structures which are practically infeasible, the bottom-level's controlled random search is to give them a very bad fitness function value, thus in the top-level's genetic algorithm, they will soon be eliminated through contest.

For the bottom-level's parameter optimization problem, the controlled random search (CRS) is adopted in our strategy. The CRS has been shown to be very robust and especially efficient approaching the global optimun. Although less efficient than gradient based methods, CRS can statistically guarantee convergence to an optimum[2,3].

The CRS algorithm involves two steps: a) Feasible point initialization; b) Stochastic search for the optimum.

a) Feasible point initialization: This is not as crucial for the CRS algorithm as for gradient-based methods. Actually, the algorithm provides a mechanism for automated initialization, in which the initial point is seeded by a random-number generator, followed by an iterative stochastic procedure to ensure feasibility. When the initial point is obtained, it must be checked for feasibility, and a new set is generated and tested, using a variant of the stochastic search method, described next, until a feasible set is located and stored in $\underline{d}^1$. This completes the first stage of the algorithm.

b) Stochastic search for the optimum: In the second stage, the CRS algorithm searches for an optimum. At iteration k, with the current decision variables $\underline{d}^{k-1}$ and new decision variables $\underline{d}^k$ are generated randomly using a Gaussian distribution with mean at $\underline{d}^{k-1}$ and standard deviation vector $\underline{\sigma}$, where:

$$\sigma_j = k_1 \min[(d_j^U - d_j^k), (d_j^k - d_j^L)], \; j = 1, \cdots, N_D, \tag{1}$$

where d_j^U and d_j^L are the upper and lower bounds for decision variable j, respectively, k_1 is a heuristic parameter, and N_D is the number of decision variables. The feasibility of each new vector $\underline{d}^r$ is checked and the objective function is evaluated. When $\underline{d}^r$ satisfies all the constraints and the objective function is reduced, $\underline{d}^k = \underline{d}^r$. When a feasible point that improves the objective function is found, a new iteration is started, updating $\underline{\sigma}$ and the iteration counter, and new values for $\underline{d}^r$ are generated. When no progress is made after a specified number of trials (i.e., after $k_2 N_D$ failures, where k_2 is a heuristic parameter), $\underline{\sigma}$ is reduced according to $\sigma_{new} = k_3 \sigma_{old}$, where k_3 is also a heuristic parameter. The iteration continues until:

$$\max_j \frac{|d_j^k - d_j^{k-1}|}{d_j^U - d_j^L} < \varepsilon, \quad j = 1, \cdots, N_D. \tag{2}$$

Based upon experience, $k_1 = 0.5$, $k_2 = 25$, $k_3 = 0.5$. A value of $\varepsilon = 0.0001$ was used to ensure adequate convergence.

Another advantage of this strategy is that it provides a series of solutions, instead of a single solution. Therefore, under the condition that the objective functions are approximately the same, some other important factors which are difficult to be expressed by objective function can be taken into account, including operability, controllability, etc., thus leading to a system which not only has a good objective function value, but also satisfies other important requirements.

3 A case study

In this section, the strategy proposed is to be applied for solving the optimization problem for a typical heat exchanger network (HEN). This optimization problem can be stated as a system of N_H hot streams of given hot inlet temperatures to be cooled to specified outlet temperatures, and N_c cold streams of given cold inlet temperatures to be heated to specified outlet temperatures, together with flowing heat capacity data for each stream. It is required to define an optimal structure of heat exchangers together with their heat transfer duties, such that the annual cost (accounting for energy and capital costs) will be minimized. The results of the optimization will be the required matchings between the hot and cold streams and the duties of the heat exchangers.

An incidence matrix is used to represent the structure of a heat exchanger network. Without loss of generality, the cold streams will be referred to as the "key" streams, while the hot streams will be termed as the "non-key" streams. In a HEN structure, the order by which streams exchange heat may be important. In order to support the ordering, the concept of "HEN level" is introduced. The number of columns in an incidence matrix is equal to the number of "key" streams, while the number of rows in an incidence matrix is equal to the number of levels in an HEN. The value k of element (i, j) means that the "key" stream j exchanges heat with the "non-key" stream k at level i. If k is equal to zero, then it indicates that the "key" stream j has no heat exchange with "non-key" stream at level i. Within the same level, every "non-key" stream can carry out heat exchange with several "key" streams. Fig. 2 shows a simple heat exchanger network and its incidence matrix. This HEN has 3 cold streams and 2 hot streams, and its number of levels is 2. To facilitate the manipulations of genetic algorithm, it is necessary to transform the two-dimensional incidence matrix into a one-dimensional string. Taking Fig. 2 as an example, its one-dimensional string is as follows: {2,2,1,1,0,2}. Obviously, the complexity can be effectively controlled by changing the number of levels, which is practically meaningful.

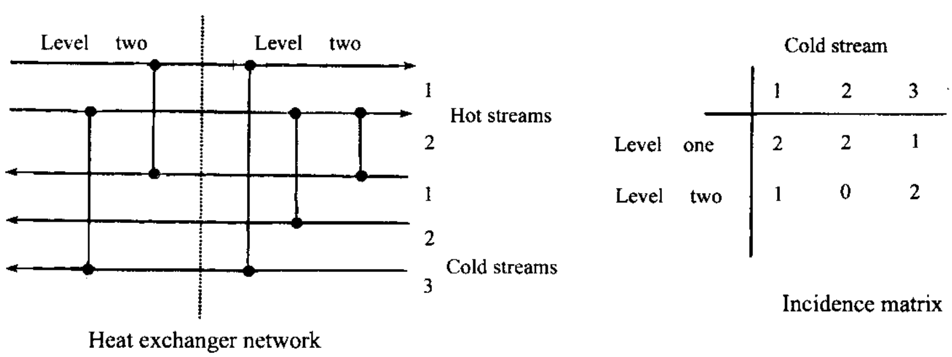

Fig. 2 A simple heat exchanger network and its incidence matrix representation

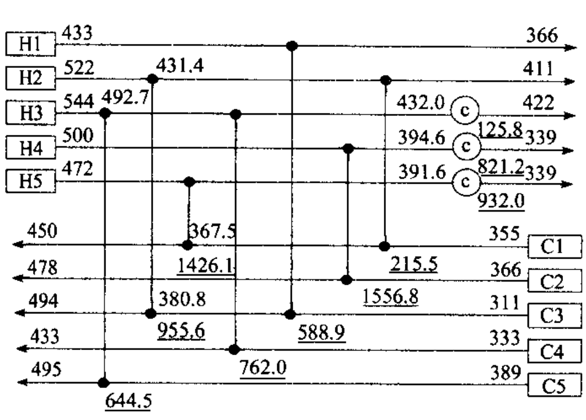

Fig. 3 The first solution to the 10spl problem

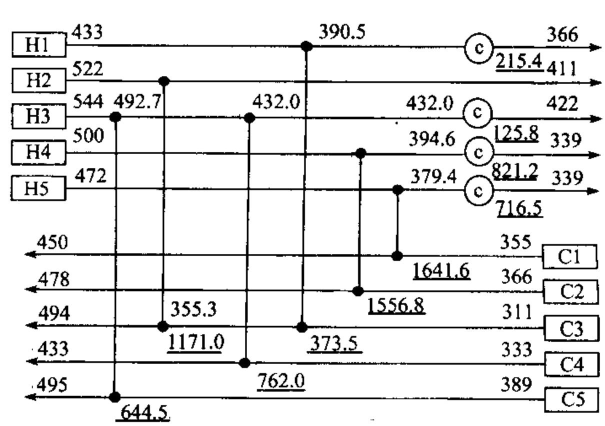

Fig. 4 The second solution to the 10spl problem

The HEN example is the 10sp1 problem which is widely used, so far the optimal annual cost to this problem is \$43 934, and the other relevant data can be found in [4]. By using the above method to solve this problem, a set of solutions can be obtained, Fig. 3 and Fig. 4, where the circles with c are coolers, are two of these solutions whose annual costs are \$43 704 and \$43 727, respectively. It is observed that as far as annual cost is concerned, these solutions are very close to each other. As stated earlier, the final decision can be made taking other factors into account, such as controllability and operability, etc.

4 Conclusion

In this paper, a new strategy for system optimization is proposed: at the top level, the genetic algorithm is used to carry out structure optimization, while at the bottom level, the controlled random search is adopted for parameter optimization for the structures provided by the top level. The top level's genetic algorithm doesn't have to deal with constrained problem when conducting structure optimization. As long as a suitable structure representation is worked out, the top-level algorithm can assign the task to the bottom-level's parameter optimization algorithm to judge whether a certain structure is feasible or not. The controlled random search is a relatively robust algorithm of global convergence, which can be used to address multivariable constrained optimization problem. Another advantage of this strategy is that it can provide a series of optimal solutions. Therefore, the final decision can be made by further taking other important factors into account. The approach is demonstrated by applying it to the optimal design of a typical heat exchanger network.

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