

Automated Design of Heat Exchangers Using Artificial Intelligence Based Optimization

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Abstract

Heat Exchangers are very important in any process industry and their optimal design is of crucial importance in terms of performance and economy. Due to several design variables and different alternatives for each variable, the design of a shell and tube heat exchanger can be posed as a large-scale discrete optimization problem. Genetic Algorithm is a non-conventional optimization technique, which scores over conventional techniques. In the present study, Genetic Algorithm is applied to the optimal design of shell and tube heat exchanger, and found to converge in very few (10) generations considering 6 design variables with a total of 4608 configurations.

Keywords: Heat Exchanger Design, Shell and Tube Exchanger, Genetic Algorithm, Optimization.

Introduction

Heat Transfer Equipment is very vital in any process industry and of this equipment, heat exchangers are the most widely used. Optimal design of such important equipment is an active area for exploring new technologies. There are conventional techniques of optimization, which apply better in certain cases while their usage is limited in others. Conventional techniques of optimization are the best means when sufficient data, mathematical models and gradient information is available and if entrapment in local optima can be avoided. But when the above cannot be ensured as in the case of many real life optimization problems, one has to look for non conventional techniques of optimization. Genetic Algorithm is one such non-Conventional optimization technique that is gaining ground in recent time (Goldberg, 1989; Davis, 1991; Wong & Wong, 1997; Babu, 1999).

Heat Exchanger design can be viewed as a discrete optimization problem because the design variables do not assume values in a continuous range, but are discrete. Due to the large number of configurations possible for a given set of process conditions, the design of heat exchangers falls under the category of large scale discrete optimization problems. The aim of the present work is to find out the configuration that would result in minimum heat exchanger area and hence the minimum cost of the exchanger (Peters and Timmerhaus., 1980). The data for the design variables is obtained from literature (Perry & Chilton, 1973)

which gives rise to a total of 4608 configurations. The study begins with a brief overview of optimization techniques and their merits and demerits. The next section deals with the Genetic Algorithm and the three Genetic Operators namely Reproduction, Crossover and Mutation. This section also deals with the problem formulation. The optimal design of shell and tube heat exchanger using GA, the approach in developing the software code in C language and the results are discussed in the subsequent sections.

Optimization Techniques

There are numerous methods available for optimization. The choice of any method depends on the suitability to the problem at hand. Conventional optimization techniques broadly consist of calculus based, enumerated and random techniques (Rao, 1984). These techniques are based on well-established theories and work perfectly well to a case wherever applicable. But there are certain limitations to the above mentioned methods. For example, the steepest descent method starts its search from a single point and finally ends up with an optimal solution. But this method does not ensure that this optimum is the global optimum. Hence there is every possibility of these techniques getting trapped in local optima, as shown in Fig. 1. Another great drawback of traditional methods is that these require complete information of objective function, its dependence on each variable and the nature of the function. These also make assumptions in realizing the function as a continuous one. All these characteristics of these traditional methods make them inapplicable to many real life problems where there is no sufficient information on mathematical model of the system, Parameter dependence and other such information. This calls for non-conventional techniques to address many real life problems. Also, optimization algorithms in engineering design are becoming popular in recent times due to the availability and affordability of high-speed computers.

Genetic Algorithm and Simulated Annealing are two such non-conventional optimization algorithms (Goldberg, 1989; Deb, 1996). These are more robust than the conventional ones. Genetic algorithm mimics the principle of natural genetics and natural selection to constitute search and optimization. Simulated Annealing mimics the cooling phenomenon of molten metals to constitute the search procedure. The operation of genetic algorithm begins with a population of random strings representing design variables. Thereafter each string is evaluated to find the fitness value. The population is then operated by three genetic operators namely, reproduction, cross over and mutation. Simulated Annealing follows the thermodynamic process of cooling of molten metals to achieve minimum Free Energy State. Simulated annealing works with a point and at every iteration creates a point according to the Boltzman probability distribution. This was applied in recent study to solve a heat exchanger design (Chaudhuri et al., 1997). For a slow simulated cooling process, this method guarantees to achieve global solutions.

Genetic Algorithm: An Overview

Professor John Holland of the university of Michigan, Ann Arbor envisaged the concept of genetic algorithm way back in 1960's (Holland, 1975). In late 1980's further developments were made and the methodology was conceptualized (Davis, 1991; Goldberg, 1989; Michalewicz, 1992). Genetic algorithms are unique by themselves and stand out from the

traditional methods of optimization. These are closely related to the natural selection and the survival of the fittest theories of Charles Darwin. There are certain striking features of GA that establishes its credibility. The most essential feature is that GAs work with a population of points instead of a single point. This enables the search to come up with a region of global solutions. Secondly, the initial population is chosen randomly. Therefore the search can proceed in any direction. GAs use probabilistic transition rules rather than deterministic procedures (Goldberg, 1989). Hence the search will be multidirectional. The various areas where simple and modified GAs have been already applied are: Computer aided molecular design using genetic algorithms (Venkatasubramanian et al., 1994), Piping systems support design (Chiba et al., 1996), DNA structure studies (Guarnieri and Mezei, 1996), On-line optimization of ethanol fermentation (Moriyama and Shimizu, 1996), HE network synthesis (Athier et al., 1997), Aircraft structure design (Dunn, 1997), Truss design (Vazquez-Espi and Vazquez, 1997), Molecular scale catalyst design (McLeod et al., 1997), Virology and AIDS studies (Shapiro and Wu, 1997), Internet studies (Joseph and Kinsner, 1997), Mutual fund (Lettau, 1997), market simulations (Price, 1997), Heat exchangers (Chaudhuri and Diwekar, 1997), Multidatabase systems (Subramanian and Subramanian, 1998), Heat transfer optimization in finned tubes (Fabbri, 1998), heat exchangers (Tayal and Fu, 1999), distillation sequences synthesis (Wang et al., 1998) and Heat transfer in trickle bed reactors (Babu and Sastry, 1999).

Genetic Operators :

The entire strength of GA lies in the three genetic operators: reproduction, crossover and mutation, which make it a robust optimization technique. The first operator, Reproduction is a process in which individual strings are copied according to their objective function or fitness. The second operator, Crossover randomly exchanges parts of genes of two parent solution strings of a generation $G(t)$ to generate the next generation, $G(t+1)$. The intuition behind the applicability of the crossover operator is information exchange among different potential solutions. Mutation is a secondary search operator, which increases the variation in population.

Reproduction is the first of the three operations done on the initial population. This is also known as selection operator, as it selects good strings from a population and forms a mating pool. The commonly used reproduction operator is the proportionate reproduction operator, where a string is selected for the mating pool with a probability proportional to its fitness. Roulette Wheel approach is followed in selecting the mating pool. It is to be noted that no new strings are created and the same strings are simply copied to the mating pool in reproduction phase. Crossover is the second operation. Some of the strings are picked from the mating pool and are altered in a manner such that some portions of the strings are exchanged between them as shown in the Fig. 2. The position of exchange is normally chosen at random and the operation is carried out with a probability called Crossover Probability P_c . If good strings are created from Crossover Operation, there will be more copies of them in the next mating pool generated by reproduction. If bad strings are created as a result of crossover, then they will not survive too long because reproduction will select against those strings in the subsequent operations.

Mutation is the final operator in a generation. Supposing we have a population of strings, which start with a 0 in first bit place, then neither reproduction nor crossover can bring

about a change in this pattern. That is, the new generations will continue to contain strings with the same 0 at first bit place. In the worst case, it may so happen that our global optimal solution needs a bit value of 1 in the starting bit position of the string, then the global optima can never be attained. To overcome this difficulty, genetic algorithm uses an operator called mutation operator, which swaps a bit from either 0 to 1 or vice-versa as shown in the Fig. 3. This mutation is carried out on a few strings only which are selected through mutation probability, P_m .

Problem Formulation:

The problem formulation of any optimization problem can be thought of as a sequence of steps. In the present study, exchanger area or the cost of the exchanger is to be optimized and the following steps are followed:

1. Choosing design variables (tube inside & outside dia, shell inner dia, no of tubes etc.,)
2. Formulating constraints (given process conditions)
3. Formulating objective function (exchanger area)
4. Setting up variable bounds (discrete values for each variable)
5. Choosing an algorithm (genetic algorithm)
6. Obtaining the solution (arriving at minimum exchanger area)

A genetic algorithm for a particular problem must have the following five components.

- A genetic representation of potential solutions to the problem
- A way to create an initial population of potential solutions
- An evaluation function that plays the role of the environment and rates solutions in terms of their fitness
- Genetic operators to alter the composition of a string
- Values for various parameters that the genetic algorithm uses (population size, probabilities of applying genetic operators, etc.,)

A genetic algorithm is a search procedure modelled on the mechanics of natural selection rather than a simulated reasoning process. Domain knowledge is embedded in the abstract representation of a candidate solution, termed an organism. Organisms are grouped in to sets called populations. Successive populations are called generations. Any string in the search space is evaluated for its fitness, depending on which the particular string is either dropped or taken into the next generation. In general, a fitness function $F(x)$ is first derived from the objective function and is used in successive genetic operations. In our case fitness function is inversely related to the area of the exchanger. Minimization problems like this one are usually transformed in to maximization problems.

For maximization problems with objective function $f(x)$, Fitness function $F(x) = f(x)$.

For minimization problems, Fitness function $F(x) = 1 / [1 + f(x)]$.

Results and Discussions

The design variables considered in the present case are tube outside diameter, tube inside diameter, pitch, shell inner diameter, no of tubes, type of the pitch, type of the HE as specified by TEMA and number of passes (Perry & Chilton, 1973). From the data obtained

from literature for the above variables, around 4608 configurations are possible. Shell side and Tube side heat transfer coefficients are calculated and the heat exchanger area is calculated according to the standard methods (Kern, 1997). Software code is developed in C language. G_{tube} , $\text{visc}_{\text{tube}}$, $C_{p_{\text{tube}}}$, K_{tube} , G_{shell} , $C_{p_{\text{shell}}}$, K_{shell} , pop_size and maximum number of generations gen are initialized. The initial population is chosen randomly using random generation function. The function $\text{cal_ht}()$ calculates the tube side heat transfer coefficient and $\text{cal_hs}()$ calculates the shell side heat transfer coefficient. $\text{cal_area}()$ is used to calculate the area of the exchanger for a given set of process conditions and a selected configuration. The function $\text{eval}()$ evaluates the potential strings for their fitness. Each string is made up of 25 binary bits representing the above mentioned design variables. A population size of 50 is chosen for this program.

The main execution of the program begins with the random initialization of a population of 50 binary strings (chromosomes) each of 25 bits (genes). All the chromosomes in the population are evaluated for their fitness and are accordingly selected to form the mating pool. Maintaining an array of probabilities proportional to the fitness of each string helps in forming the mating pool. A range of cumulative probabilities for each string is generated based on individual string probabilities. This cumulative probability ranges from 0 to 1. Random numbers from 0 to 1 are generated and the strings are selected to form the mating pool, corresponding to each random number. After Reproduction, crossover and Mutation are carried out with the corresponding probabilities. For this study both crossover and mutation probabilities are taken to be 0.25. The above three operations are repeated until the condition of the maximum number of generations is met. The flow chart shown in Fig. 4. gives the basic outline of the program. The design variables and various possible alternative configurations are listed in Table-1.

Case Study:

For a specific design problem where the aim is to arrive near the optimal region of exchanger area, it is found that the Convergence is obtained in a very few generations (10). The various data considered are listed in Table-2 and Table-3 for tube side and shell side respectively. All the quantities are taken in FPS system of units.

For a case where maximum no of generations are 10, the average fitness of each generation is calculated and is shown in Table-4. Genetic Algorithms belong to the class of probabilistic algorithms, but they are very different from random algorithms as they combine elements of directed and stochastic search. Hence the optimal regions obtained in a few generations itself as shown in the Fig. 5.

Conclusions

In the present study, heat exchanger design, which is a discrete optimization problem, is attempted using genetic algorithm. A total of 4608 configurations constitute the search space when 6 design variables are considered and it is found that the algorithm converges to the minimum exchanger area configuration in only a few generations. In fact the best approach to any optimization problem is to first come near to global Optimal region using Genetic Algorithm and then use any well-established conventional optimization technique to achieve the exact global optimal solution. The successful application of Genetic

Algorithm to the problem discussed here proves the authenticity of this algorithm in various real life applications.

Nomenclature

G_{tube} Tube side Mass velocity
visc_{tube} Tube side viscosity
Cp_{tube} Tube side Heat Capacity
K_{tube} Tube side thermal conductivity
G_{shell} Shell side Mass Velocity
Cp_{shell} Shell side Heat Capacity
K_{shell} Shell side thermal conductivity
pop_size Population size
GA Genetic Algorithm
Pc Crossover Probability
Pm Mutation Probability
G (t) tth generation
G(t+1) (t+1)th generation
F (x) Objective function
F (x) Fitness function
TEMA Tubular Exchanger Manufacturers Association
LMTD Log Mean Temperature Difference
shell_id Inner diameter of shell
tube_od Outer diameter of tube
tube_id Inner diameter of tube

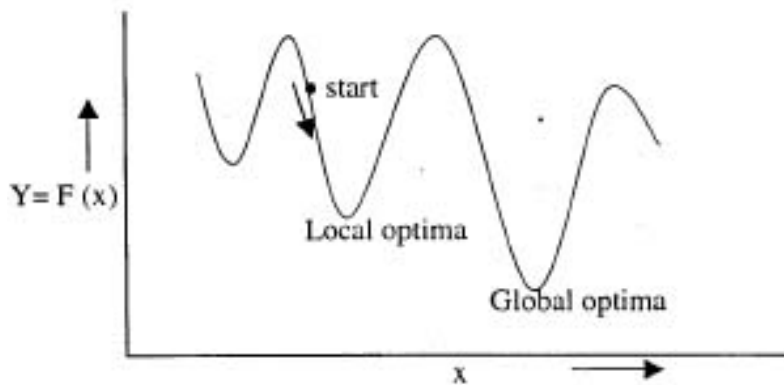


Fig. 1. Entrapment of Conventional method in local optima

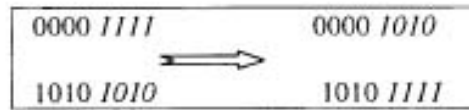


Fig. 2. Crossover operation

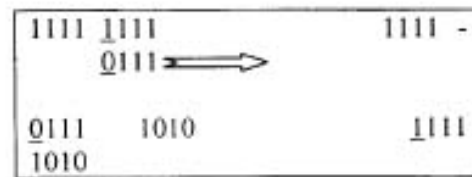


Fig. 3 Mutation operation

Table-1. Design Parameters

Design Variable	Alternatives
Shell_id	18
TEMA Type	2 (P or S and U)
No of Passes	4
Pitch	2
Tube_od	4
Tube_id	4

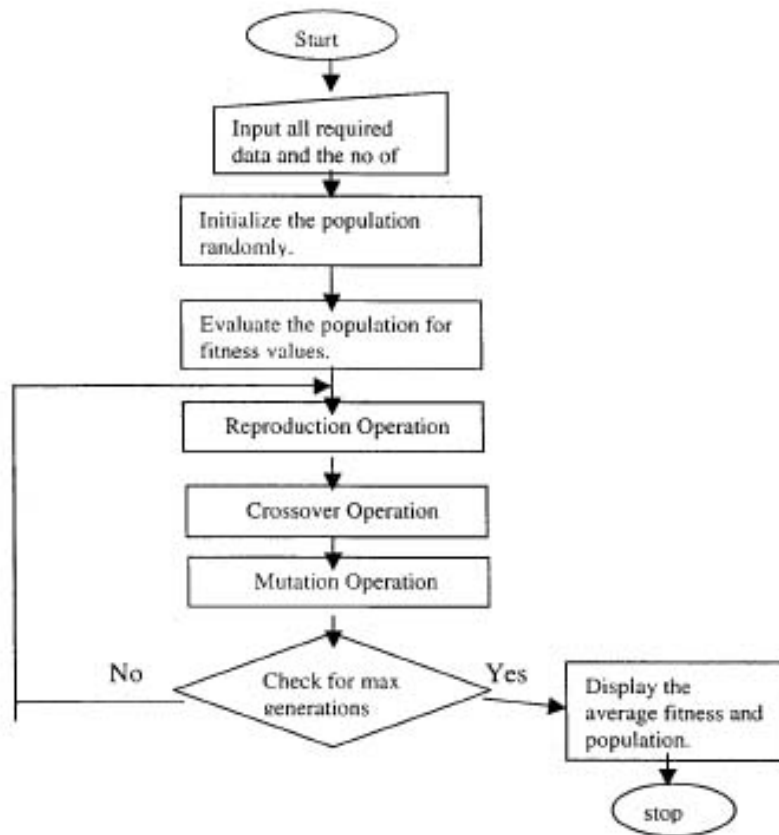


Fig. 4. Flowchart for the program

Table-2. Tube side data:

Mass Velocity	149000 lb/ft ² -hr.
Viscosity	8.70 lb/ft-hr.
Heat Capacity	0.49 Btu/lb-°F.
Thermal Conductivity	0.077 Btu/ft-hr-°F.

Table-3. Shell side data:

Mass Velocity	43800	lb/ft ² -hr.
Viscosity at wall temp	0.97	lb/ft-hr.
Viscosity at bulk temp	0.59	lb/ft-hr.
Heat Capacity	0.87	Btu/lb-°F.
Thermal Conductivity	0.0765	Btu/ft-hr-°F.

Table-4. Average fitness for 10 generations

Generation Number	Average Fitness
1	2.657860
2	2.657862
3	2.657857
4	2.657859
5	2.657861
6	2.657863
7	2.658012
8	2.658015
9	2.801361
10	2.801361

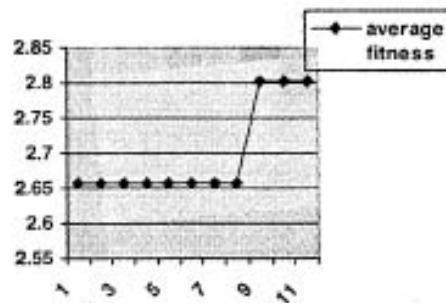


Fig. 5. Average Fitness Versus Number of Generations

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