Optimization of Shell and Tube Heat Exchangers Using modified Genetic Algorithm

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Abstract

The objective of this paper is to Develop and Test a model of optimizing the early design phase of shell and Tube Heat Exchangers via the application of modified Genetic Algorithm (MGA).The Modified Genetic Algorithm is based on the integration of classical genetic algorithm structure and a systematic neighborhood structure .The MGA model can help the designers to make decisions at the early phases of the design process. With a MGA model, it is possible to obtain an approximately better prediction, even when required information is not available in the design process. This model proved that MGA is capable of providing better solutions with higher quality even with inadequate data.

Keywords: *Shell and Tube Heat Exchangers, Modified Genetic Algorithms, Cost Estimation*

1. Introduction

Designing a product deals with various parameters such as cost, time, size, area, accuracy etc. among the above cost estimation is a key factor during the development phases of manufactured products. Early approximations of cost depend on the structure and development of the product. The more the size of product the more cost it provides. Studies have shown that the greatest potential for cost reduction is at the early design phases, where as much as 80% of the cost of a product is decided. The total development cost provides a greater effort for the designer to design and it is necessary to step towards optimizing the product. Making a wrong decision at this stage is extremely costly and further down the development process. Product modifications and process alterations are more expensive in the upcoming development cycle. Thus, cost estimators need to approximate the true cost of producing a product, in addition optimization has to be done in parallel. Rush et all. [10] examine both traditional and more recent developments in cost estimating techniques in order to highlight their advantages and limitations. The analysis includes parametric estimating; feature based costing, artificial intelligence, and cost management techniques. Niazi et all. [11] provide a detailed review of the state of the art in product cost estimation covering various techniques and methodologies developed over the years. The overall work is categorized into qualitative and quantitative techniques. The qualitative techniques are further subdivided into intuitive and analogical techniques, and the quantitative ones into parametric and analytical techniques. Curran et all. [12] provide a comprehensive literature review in engineering cost modeling as applied to aerospace. The basic approaches that are used in general are summarized below:

Analogy-based techniques: these techniques are based on the definition and analysis of the degree of similarity between the new product and another one, which has been already produced by the firm.

The parametric method: the cost is expressed as an analytical function of a set of variables that consist or represent some features of the product which are supposed to influence mainly the final cost of the product. These functions are called Cost Estimation Relationships (CERs) and are built using statistical methodologies.

Analytical Models: in this case the estimation is based on the detailed analysis of the manufacturing process and of the features of the product. The estimated cost of the product is calculated in a very analytical way, as the sum of its elementary components, constituted by the value of the resources used in each step of the production process (raw materials, components, labor, equipment, etc. Due to this, the engineering approach can be used only when all the characteristics of the production process and of the product are well defined.

Therefore, the application of this approach is limited to situation where a great amount of input data is available. In the MGA analytical model is used. In this algorithm the tube diameter, viscosity of the liquid, heat specific capacity, temperature, Thermal conductivity and Mass flow rate are mentioned. So with this all above mentioned parameters the estimation is done by using analytical Methodologies.

2. Modified Genetic Algorithm (MGA)

Genetic algorithms (GAs) are stochastic optimization techniques founded on the concepts of natural selection and genetics. The algorithm starts with a set of solutions called population. Solutions from a population of chromosomes are used to form a new population. Once the initial population is formed, the GA creates the next generation using three main operators: (1) reproduction, (2) crossover and (3) mutation**.** Reproduction is the process in which the most fits chromosomes in the population receives correspondingly large number of copies in the next generation. This operation increases quality of the chromosomes in the next generation and therefore leads to better solutions of the optimization problem. The crossover operator takes two of the selected parent chromosomes and swaps parts of them at a randomly selected location. This provides a mechanism for the chromosomes to mix and match their desirable qualities in forming offspring. Mutation plays a secondary role in the GA to alter the value of a gene at a random position on the chromosome string, discovering new genetic material or restoring last material. New solutions are selected according to their fitness: the more suitable they are, the more chances they have to reproduce. This produce repeated until some condition is satisfied. With crossover and mutation taking place, there is a high risk that the optimum solution could be lost as there is no guarantee that these operators will preserve the fittest string. To counteract this, elitism mechanism is often used. In this mechanism, the best individual from a population is saved before any of these operations take place. After the new population is formed and evaluated, it is examined to see if this best structure has been preserved. If not, the saved copy is reinserted back into the population. Using selection, crossover, and mutation on their own will generate a large amount of different probable solutions. However, some main problems can arise. Depending on the initial population chosen, there may not be enough diversity in the initial solutions to ensure the GA searches the entire problem space.

Furthermore, the GA may converge on sub-optimum solutions due to a bad choice of initial population. Moreover, inappropriate operator rates can destroy good solutions and degenerate the GA into a random search. These problems may be overcome by the introduction of an improvement mechanism into the GA. In this paper, for the new solutions, an optimization algorithm based on the integration of classical genetic algorithm structure and a systematic neighborhood structure is employed to achieve more effective search. The neighborhood unit performs two main tasks: (i) receive the best solution found and obtain the neighbor solutions for this best solution, (ii) find a new best solution with more high quality if it is possible. Since this strategy suggests the solution diversity, all of the probable solutions with higher quality can be searched. The outline of the MGA used in this paper is given below:

```
initialize population;
while predetermined termination condition not satisfied;
{
evaluate chromosomes in population;
keep the best solution;
obtain the neighbor solutions for the best solution;
compare the best solution and best neighbor solution;
keep the new best solution;
reproduction;
apply crossover and mutation to chromosomes in population;
new population = population + new best solution;
}
```

This mechanism searches the all neighbouring solution space for the existing best solution and provides to increase of genetic diversity leads to effectiveness of the algorithm. Because of the problem type and the use of neighborhood mechanism in the presented algorithm structure, binary coded genetic algorithm was preferred. At each generation of GA search, there are a lot of neighbor chromosomes of the chromosome with high quality. When the all neighbor solutions of the existing chromosome are evaluated by the algorithm, faster convergence with finer tuning could be achieved, and a considerable improvement in the solution quality could be obtained. To overcome the local optimality problem, the use of the crossover and mutation operators is important. It is noted that the crossover and mutation operators are applied to the new population stated by population and new best solution. Thus, the probability of the search trapped in a local optimum can be considerably eliminated. The neighborhood of a solution is the set of all formations that can be arrived at by a move. The move is a process that transforms the search from the current solution to its neighboring solution.If, after making a move, a solution is found which is better than all solutions found in prior moves than the new solution is saved as the new best solution.

This neighborhood procedure is applied to best only one solution of the each generation. Considering a chromosome with n bits, the number of the neighbor solutions is n, as depicted in Figure 1. To obtain the neighbor solutions for the best solution, encoding and decoding operations are applied. In this work, different bit sizes are tried to achieve a good balance between the algorithm performance and the computational cost, and we finally adopt a bit size of 8. According to simulation results, this bit size is suitable for the main process in the algorithm described in this paper.

Real coded	Binary coded(8 bits)	Decoding
Best solution: 2.391 (Encoding) →	0 1 1 1 0 1 1 1	
Neighbour solutions	1 1 1 1 0 1 1 1	4.846
	0 0 1 1 0 1 1 1	1.157
	0 1 0 1 0 1 1 1	1.772
	0 1 1 0 0 1 1 1	2.079
	0 1 1 1 1 1 1 1	2.540
	0 1 1 1 0 0 1 1	2.310
	0 1 1 1 0 1 0 1	2.348
	0 1 1 1 0 1 1 0	2.368

Figure 1. Neighbourhood structure for the best solution.

3. Heat Exchanger Design

Shell-and-tube heat exchangers are probably the most common type of heat exchangers applicable for a wide range of operating temperatures and pressures. They have larger ratios of heat transfer surface to volume than double-pipe heat exchangers, and they are easy to manufacture in a large variety of sizes and flow configurations. They can operate at high pressures, and their construction facilitates disassembly for periodic maintenance and cleaning. Shell-and-tube heat exchangers find widespread use in refrigeration, power generation, heating and air conditioning, chemical processes, manufacturing, and medical applications.

A shell-and-tube heat exchanger is an extension of the double-pipe configuration. Instead of a single pipe within a larger pipe, a shell and-tube heat exchanger consists of a bundle of pipes or tubes enclosed within a cylindrical shell. One fluid flows through the tubes, and a second fluid flows within the space between the tubes and the shell . The main purpose of a heat exchanger is to capture heat that would otherwise be lost through waste gases or liquids and return that heat to some stage of the production process. Heat exchangers have been used in various industrial processes for more than 60 years. The most commonly used type of heat exchanger is the shell-and tube heat exchanger, the optimal design of which is the main objective of this study. Various strategies are applied for the optimal design of heat exchangers. The main objective in any heat exchanger design is the estimation of the minimum heat transfer area required for a given heat duty, as it governs the overall cost of the heat exchanger. However there is no concrete functioning that can be expressed explicitly as a function of design variables and in fact many numbers of discrete combinations of the design variables are possible. Early cost estimate of a part is important information and forms a basis for preparing quotations, which are competitive from a market point of view. The cost of any highly engineered product is impacted significantly by decisions made at the design phases. While this influence decreases though all phases of the life cycle, the committed costs increase. It is seen that a commonly adopted approach of variant cost estimation based only on geometric information of the component is not always accurate. Traditional cost estimating methods for the different phases of a project can be observed in the literature, including: traditional detailed breakdown cost estimation; simplified breakdown cost estimation; cost estimation based on cost functions; activity based cost estimation; cost index method; and expert systems. While traditional cost estimating makes use of blueprints and specifications, comparative cost estimating assumes a linear relationship between the final cost and the basic design variables of the project.

By the emergence of Artificial Intelligence (AI) tools (i.e., neural networks) possible multi- and non-linear relationships can now be investigated. Several authors have concluded that the area of the exchanger bears a strong relation to the total cost and while it considerably impacts the cost, therefore, the estimation of the cost of purchase is usually based on estimations of the heat transfer surface, and on earlier knowledge and experience of exchanger manufacturing. In addition, the shell diameter and tube diameter also become important factors influencing directly the area of the exchangers under development. At the other hand, the pitch and configuration of the bundle are also clearly important factors for the cost of the new heat exchanger. Finally, the heat exchanger type is identified as one of the main key parameters; Types of the exchanger are classified by TEMA with a well-known nomenclature. Accordingly, a shell and tube exchanger is divided into three parts: the front end, the shell, and the rear head.

4. Generalized Design Procedure for Heat Exchanger

The *design of a process heat exchanger* usually proceeds through the following steps (Perry & Green, 1993):

• Process conditions (stream compositions, flow rates, temperatures, pressures) must be specified.

• Required physical properties over the temperature and pressure ranges of interest must be obtained.

• The type of heat exchanger to be employed is chosen.

• A preliminary estimate of the size of the exchanger is made, using a heat transfer coefficient appropriate to the fluids, the process, and the equipment.

• A first design is chosen, complete in all details necessary to carry out the design calculations.

• The design chosen is now evaluated or rated using analytical model so as to its ability to meet the process specifications with respect to both heat duty and pressure drop.

• Based on this result a new configuration is chosen if necessary and the above step is repeated.

If the first design was inadequate to meet the required heat load, it is usually necessary to increase the size of the exchanger, while still remaining within specified or feasible limits of pressure drop, tube length, shell diameter, etc. This will sometimes mean going to multiple exchanger configurations. If the first design does not use the entire allowable pressure drop, a less expensive exchanger can usually be designed to fulfill process requirements.

• The final design should meet process requirements (within the allowable error limits) at lowest cost. The lowest cost should include operation and maintenance costs and credit for ability to meet long-term process changes as well as installed (capital) cost. Exchangers should not be selected entirely on a lowest first cost basis, which frequently results in future penalties.

The flow chart given in Fig 2. gives the sequence of steps and the loops involved in the optimal design of a shell-and-tube heat exchanger using MGA.

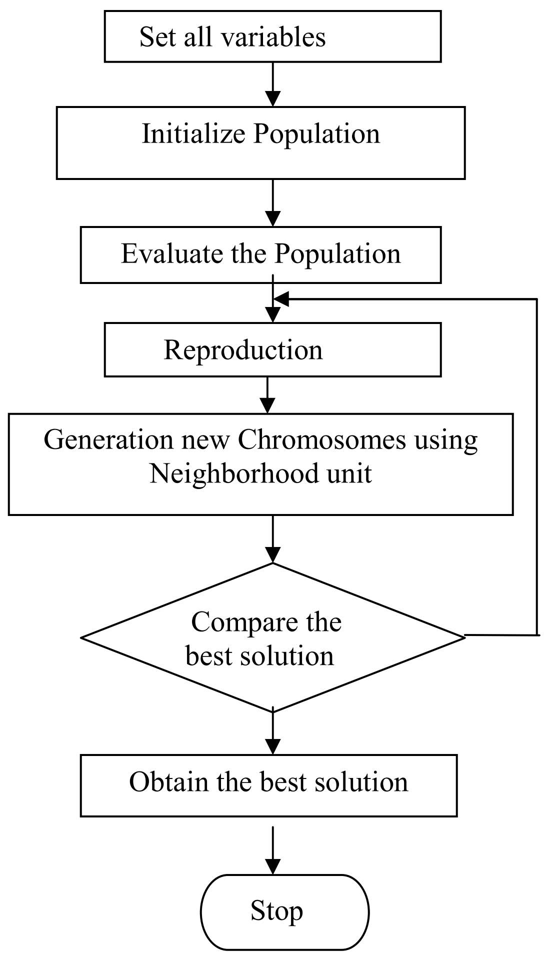


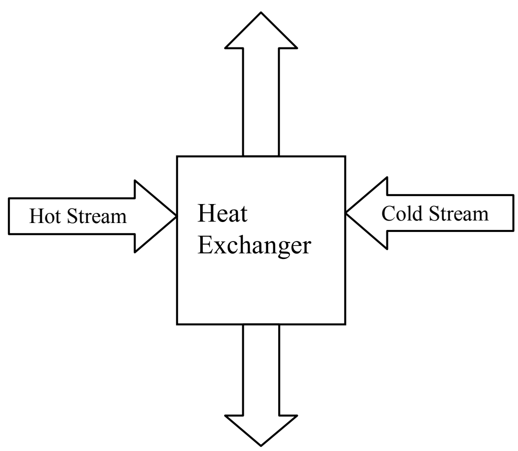
Fig 2. Flowchart of Modified Genetic Algorithm.

5. Optimization

The Proposed approach of Modified Genetic Algorithm uses a solution which is more suitable for one of the three operators named “reproduction”. Reproduction of new chromosomes is developed until some condition is satisfied. To make the above said true,”elitism” mechanism is used. In this mechanism, the best individual chromosome species from a population is saved before any of these operations take place. Then the new generation chromosomes are developed until the condition set for their generation is satisfied. In the Modified genetic Algorithm, we make use of classical genetic algorithm which concentrates on the reproduction side and neighborhood unit concentrates on receiving and regenerating the new best solution with more high quality. By the use of Modified Genetic Algorithm , lot of neighbor chromosomes solutions with higher quality is obtained when these solutions are evaluated using an algorithm, faster convergence and fine tuning together with improvement in the solution quality can be achieved.

6. Results and Discussions

The model and design data’s for the above algorithm is shown in Figure 3.



T^hin=368.15K	T^cin=298.1K
T^hout=313.15K	T^cout=313.1K
m^h=27.78 kg/s	m^c=0.033kg/s
k^h=0.19W/mK	k^c=0.59W/mK
ρ^h= 995 Kg/m^3	ρ^c=995Kg
Cp^h=2840 kJ/KgK	Cp^c=4200kJ /KgK
μ^h=0.00034 cP	μ^c= 0.0008 cP

Figure 3. Model of Heat exchanger and Design datas

For this above example, a constraint in the tube length of 4.88m was imposed.

Summary of the result obtained with the proposed model is given in the table where the Standard solution by normal Genetic Algorithm is compared with the solutions of the modified Genetic Algorithm. It can be observed that the proposed algorithm provided a better solution than the standard solution. This shows that the proper use of MGA can provide a global optimum solution. For the above problem, we used a population of 45 individuals and obtained the final solution in 40 minutes of real time.

7. Conclusion

In this work, an optimization model for the design of shell and tube exchanger using Modified Genetic Algorithm has been proposed. The optimization strategy uses MGA which is formed by the Integration of Classical Genetic Algorithm and Neighborhood units. GA are in general more effective in producing optimum solutions and when this Algorithm is combined with Neighborhood units optimum solutions with best and high quality is achieved. Table 1. Gives the optimization results of Heat Exchanger.

	Standard GA	MGA
Area(m^2)	242.881	244.251
U(W/m^2k)	714.511	698.264
No. of tubes	653	620
Tube layout	Triangle	Triangle
No. of tube passes	6	10
No. of baffles	8	8
Hot fluid allocation	Tube	Tube
Shell diameter(m)	1.1053	1.432
Tube length(m)	4.88	4.88
Baffle spacing (m)	0.516275	0.5128

Table 1.Optimization result.

The result of the case study ends up with the final conclusion that the use of MGA provides the best solutions with higher quality together with short duration of real time. In future the same analysis can be used to generate better solutions with higher quality with various types of liquids (Miscible and Immiscible).

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Nomenclature

T^hin= Input Temperature of Hot liquid (K).
T^cin= Input Temperature of cold liquid (K).
T^hout= Output Temperature of Hot liquid (K).
T^cout= Output Temperature of Cold liquid (K).
m^h=Mass flow rate of Hot Liquid (kg/s).
m^c= Mass flow rate of Cold Liquid (kg/s).
k^h= Thermal Conductivity Hot Liquid(W/mK)
k^c= Thermal Conductivity Cold Liquid (W/mK)
ρ^h= Density of hot liquid (Kg/m^3).
ρ^c= Density of cold liquid (Kg/m^3).
Cp^h= Specific Heat Capacity of Hot Liquid (kJ/KgK).

Cp^c=Specific Heat Capacity of Cold Liquid (kJ/KgK).
μ^h= Viscosity of hot liquid (cP) .
μ^c= Viscosity of cold liquid (cP).