# Development of a New Approach for Synthesizing Heat Exchanger Networks to Save Energy in Chemical Plants

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*Abstract:* Process integration is of critical importance in achieving increased energy efficiency in industry. Heat Exchanger Network Synthesis (HENS) is one of the most efficient process integration tools to save energy in chemical plants. In this work an optimization framework is proposed for the synthesis of HENS, based on a genetic algorithm (GA) coupled with a commercial process simulator. The use of a simulator facilitates the formulation of rigorous models for different process alternatives, while the genetic algorithm allows the solutions of the complex non-convex mathematical problem, involving discrete and continuous decisions. The model uses a promising superstructure that includes the most common heat exchanger structures, and optimizes utility costs, the number of units and heat exchanger areas simultaneously. Applying the new simulation based approach to the model allowing non-isothermal mixing makes it possible to find truly optimal network configurations. The performance of the proposed approach is demonstrated using several case studies, and the obtained solutions are compared with those available in literature.

*Key-Words:* Energy Saving, Heat Exchanger Network Synthesis, Superstructure, Genetic Algorithms, Process Simulation, Process optimization

## 1 Introduction

Heat Exchanger Network Synthesis (HENS) problems have attracted significant researches due to the large saving achievable in terms of energy costs. As energy costs continue to increase, industry will have greater incentive to apply heat integration as broadly as possible in its facilities. The heat exchanger network is an arrangement of heat exchangers; in which cold & hot process streams and hot & cold utility streams interchange energy. The purpose of the HEN is to recover energy from the hot process streams to heat up cold process streams using the least amount of hot and cold utility streams, while achieving specified outlet target temperatures of the process streams.

For the first time [1] defined the heat exchanger network design problem in a rigorous manner. They proposed minimization of the total cost for designing an optimum heat exchanger network. Since then, many design algorithms have been proposed which can be found in thorough reviews of [2] and [3]. Although there have been many publications on the design of heat exchanger networks during the past four decades, the problem is still open for further research.

In general, HENS can be solved by either sequential or simultaneous approaches. Sequential synthesis methods involve partitioning the basic problem according to its temperature range and decomposing it further into various target sub-problems, each solved sequentially subject to the solution of the prior target. So these approaches often lead to suboptimal designs. On the other hand, simultaneous methods are concerned with the basic HENS problem with little or no decomposition into target subproblems. These approaches can themselves be classified as either superstructure-based framework ([4], [5]) or nonsuperstructure-based framework ([6], [7] and [8]). The model presented in this work is based on the superstructure-based framework.

From the optimization point of view simultaneous heat exchanger network synthesis methods are often formulated as mixed-integer nonlinear programming (MINLP) models, in which binary variables represent the existence of heat exchangers and continuous variables represent process parameters. Recent work by [9] has shown that solving HENS are NP-hard of strong sense. This limits the usefulness of deterministic methods such as Generalized Benders Decomposition (GBD, [10]) and Outer Approximation (OA, [10]), since their computation time increases exponentially with problem size. Thus stochastic methods such as Simulated Annealing (SA, [11]), Tabu Search (TS, [12]) and Genetic Algorithms (GA, [6], [13], [14]) are important approaches for tackling large-scale problems. Since GAs keep track of a population of potential solution, thus they are less sensitive to arbitrary initial guesses of the solution and therefore, genetic algorithm is used as the optimizer of this work.

On the other hand the classical synthesis of a HEN assumes and keeps all design conditions a constant value and the effect of temperature and pressure on physical properties of streams is neglected. This consideration can achieve solutions very far from the point of view of industrial application. So there has yet to be a proposal for a truly complete formulation of the HENS problems without any simplifying assumptions [3].

The objective of this paper is to achieve this goal by eliminating the simplifying assumption of the superstructure and using a commercial simulator. These simulators include a variety of highly efficient rigorous thermodynamic models and design models that allow the process engineer to evaluate different flowsheets and modeling options in an easy way. So taking into account the black-box model concept, the use of simulators can help to ease the formulation of the synthesis problem.

Moreover, the new approach used in this work can facilitate the incorporation of HENS concepts with other aspects of the process synthesis like distillation sequences and reactor network synthesis to lead to simultaneous synthesis of total process flowsheet.

## 2 Genetic Algorithm

Genetic algorithms are among the most widely used stochastic search algorithms and represent a promising alternative to gradient-based optimization techniques for certain classes of problems, e.g., optimization problems characterized by mixed continuous-discrete variables and discontinuous and/or non-convex system spaces ([15]). Empirically and to some extent theoretically it has been proven that GAs can provide robust search in complex spaces even if the objective function is not continuous or smooth. So they can be suitable candidates to solve large combinatorial optimization problems like the HEN synthesis.

The genetic code used here is based on the binary representation, in which each decision variable is encoded as a bit. The strong preference for using binary representation of solutions in the genetic algorithms is typically derived from the schema theory of genetic algorithms, which tries to analyze genetic algorithms in terms of their expected schema sampling behavior. Furthermore, binary representation is a robust and suitable method for MINLP problems, since every integer variable in the model can be handled efficiently by using just one bit.

In this work the genetic algorithm includes some of the most commonly accepted strategies to improve the performance of a basic GA, such as mutation, crossover and elitism and the termination criterion of the algorithm is based on the satisfaction of the pre-determined similarity ratio.

## 3 Creating Structures

To create different heat exchanger network structures, it is necessary to determine the frameworks like type of superstructure and the relationship between optimizer, user and simulator.

### 3.1 Superstructure selection

Ciric and Floudas ([4]) combined the transshipment model of Papoulias and Grossmann for the match selection with the NLP model to determine the minimum investment cost network into one MINLP formulation for a specified minimum temperature difference. This method consists of one single stage optimization in which all variables are optimized simultaneously. The hyperstructure used by the authors is shown in Fig. 1. While this hyperstructure embeds all different alternative structures, it involves more non-linear heat balance constraints and is therefore more difficult to solve.

At the same time, a stage-wise simplifies superstructure formulation has been developed by Yee and Grossmann ([5]). This method does not rely on any division into temperature or enthalpy intervals and features linear constraints from the following assumptions:

- isothermal mixing,
- no split stream flowing through more than one exchanger
- utilities at the end of the superstructure
- no stream bypass

The superstructure presented by [5] is shown in Fig. 2. At each stage in the superstructure, each hot stream is split into the number of cold streams and one possible heat exchanger is placed at every branch. As shown, utilities are located at the end of the superstructure. The number of stages in the superstructure can be set for instance to the maximum of hot or cold streams. Even though some HEN structures cannot be generated by the model, [5] illustrated that good HEN structures can be obtained. In the present work Yee–Grossmann super-structure is used as the framework, and due to using a robust optimizer coupled with a black box model the isothermal assumption of their formulation is eliminated to obtain more reliable networks.

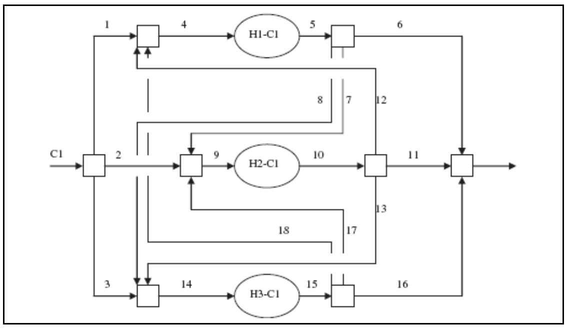


Fig. 1. The hyperstructure presented by [4]

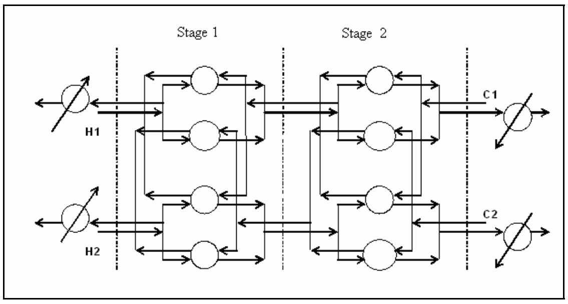


Fig. 2. The superstructure presented by [5]

### 3.2 Implementing the model

The commercially available simulators enable the detailed economical evaluation of a process flowsheet, but the inclusion of the process structure in an internal optimization step is not possible without varying the structure by hand. So, in the architecture used in this work, the user interacts with the GA defining the parameters of the algorithm, explicit constrains and convergence options, with the simulator, to select the mathematical models, and with the interphase, to set up the control variables. The chromosome used in genetic algorithm consists of two part, the first bits corresponds to the binary variables, i.e. the existence of a specified heat exchanger in the network; if the value of the bit is one, this exchanger would be added through the ActiveX capability of the simulator to the flowsheet and if the value is equal to zero, there would be no such exchanger. The remaining part of the chromosome corresponds to continuous variables which are heat exchanger duties and the split ratio of the hot and cold streams. After encoding the chromosome, the values are transferred to the simulator. The simulation is run and objective function is calculated. Then the genetic algorithm receives the objective function information and through using different operators develops other networks. This process continues until the termination criterion is satisfied. Then the optimal network and its corresponding variables are reported to the user.

Penalty functions have been used to handle the constraints in the model. A large penalty is defined for simulations ending with warnings or errors (infeasible designs), whereas a smaller penalty was used for successful simulations that did not achieve the desired specifications (e.g. a desired temperature).

## Case Studies

The performance of the algorithm is evaluated with several HENS from the literature: two small-scale and two mid-scale. The examples are organized according to size, such that the smallest problem is the first one and the last is the largest problem.

The objective is to minimize the annualized cost expressed as the sum of the utility costs, fixed charges for each heat exchanger and an area-based cost for each heat exchanger. All calculations were carried out using a P-IV CPU (1.8 GHz) with 1 GB RAM.

### 4.1 Case Study A

This example is taken from [16] and involves one hot and two cold streams. Its problem data as well as exchanger cost equations are presented in Table1. In all case studies unites used for T, Fcp, h and Cost are K, kW /K, kW/cm^2 and $/kW yr respectively.

To solve this example a superstructure with two stages is selected and so there would be 4 binary variables and 12 continuous variables, but due to existence of just one hot stream, the number of continuous variables would be decreased to 8. The corresponding chromosome length is equal to 74. The convergence is achieved in generation number of 260 by a similarity ratio of 0.95. Fig. 3 shows the final network. The numbers shown in this figure and other case studies represent the area of heat exchanger in square meter. The final network consists of two process heat exchanger and one cooler and consumes 169 kW cold utility (cooling water). This optimal network minimizes the total annualized cost to $50561, while the corresponding number in the reference paper is $53117. If the reported network is simulated by the simulator, the annual cost would increase to $53120. It should be considered that part of this difference can be caused by the approximations used in calculating the average heat capacity.

## 4.2 Case study B

This is a well known case study taken from [5] and involves two cold and two hot streams. Table 2 shows the problem data as well as exchanger cost equations. By selecting the number of stages equal to 2, the number of binary and continuous variables would equal to 8 and 16. The final network is presented in Fig. 4. This network consists of four process heat exchanger and one cooler. The total annual cost is $75890, while the reported annual cost in the reference paper is $80274.

## 4.3 Case study C

This example is taken from [13] and involves five hot and one cold streams. Its problem data as well as exchanger cost equations are presented in Table3. As it is shown in this table the corresponding temperature for the hot utility i.e. steam is 700 Kelvin, but in steam table there isn't such saturated steam. This problem shows that although in many approaches the heat exchanger network synthesis is solved just using mathematical models and the process insights is neglected, but in practice the problem can not be solved just using mathematical formulations. Anyway to synthesis this problem it is assumed that at first the hot stream is cooled to be saturated and in saturation temperature it exchanges heat with cold streams.

If for simplicity the number of stages is assumed to be 2, there would be 10 and 30 binary and continuous variables. The genetic algorithm converges to total annual cost of $375100, while Lewin has reported $573205. It is obvious that the comparison between these numbers is not logical, since the cold stream C1 can not be heated to 660 K. The final network with corresponding areas of exchangers is presented in Fig.5.

## 4.4 Case study D

This case study is also taken from [13] and it involves five cold and five hot streams. Table 4 shows the problem data as well as exchanger cost equations. By selecting the number of stages equal to 3, the number of binary and continuous variables would equal to 75 and 225. The final network is presented in Fig. 6. This network consists of 8 process heat exchangers and 3 coolers. The total annual cost is $44477, while the reported annual cost in the reference paper is $43452. There was an interesting point in running the code for this case study; i.e. after running the genetic algorithm for several times no feasible solution obtained, therefore a migration operator was used. This result is not far from expectation, since it is obvious that the efficiency of superstructure-based methods decreases by the increase of problem size. For example in this case study the number of variables is equal to 300 and the corresponding chromosome length is 1662 and migration operator should be used to give the solution.

Table 1. Problem data for case study A

| Stream | TIN | TOUT | Fcp | h | Cost |
|---|---|---|---|---|---|
| H1 | 423 | 318 | 20 | 2 | - |
| C1 | 333 | 393 | 13 | 2 | - |
| C2 | 293 | 393 | 12 | 2 | - |
| S1 | 483 | 483 | - | 1 | 80 |
| W1 | 278 | 288 | - | 1 | 20 |

Heat exchanger ($ per year), $4000 + 700a^{0.8}$;
Heat exchanger utils. ($ per year), $4000 + 560a^{0.8}$

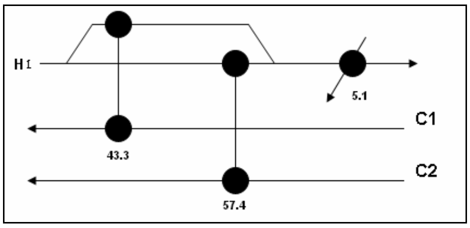


Fig. 3 The final optimal network of case study A

Table 2. Problem data for case study B

| Stream | TIN | TOUT | Fcp | h | Cost |
|---|---|---|---|---|---|
| **H1** | 443 | 333 | 30 | 0.8 | - |
| **H2** | 423 | 303 | 15 | 0.8 | - |
| **C1** | 293 | 408 | 20 | 0.8 | - |
| **C2** | 353 | 413 | 40 | 0.8 | - |
| **S1** | 450 | 450 | - | 0.2 | 80 |
| **W1** | 293 | 313 | - | 0.8 | 20 |

Heat exchanger except heaters ($ per year), $4000 + 700a^{0.8}$

Heaters ($ per year), $4000 + 560a^{0.8}$

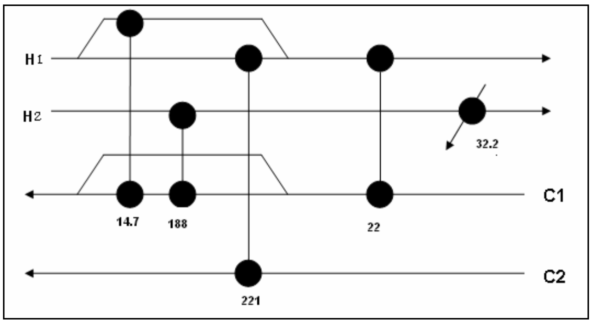


Fig. 4 The final optimal network of case study B

Table 3. Problem data for case study C

| Stream | TIN | TOUT | Fcp | h | Cost |
|---|---|---|---|---|---|
| **H1** | 500 | 320 | 6 | 1 | - |
| **H2** | 480 | 380 | 4 | 1 | - |
| **H3** | 460 | 360 | 6 | 1 | - |
| **H4** | 380 | 360 | 20 | 1 | - |
| **H5** | 380 | 320 | 12 | 1 | - |
| **C1** | 290 | 660 | 18 | 1 | - |
| **S1** | 700 | 700 | - | 1 | 140 |
| **W1** | 300 | 320 | - | 1 | 10 |

Heat exchanger ($ per year), $4000 + 700a^{0.8}$

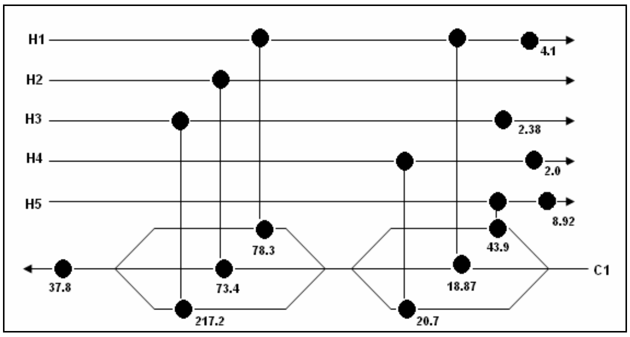


Fig. 5 The final optimal network of case study C

Table 4. Problem data for case study D

| Stream | TIN | TOUT | Fcp | h | Cost |
|---|---|---|---|---|---|
| **H1** | 423 | 366 | 8.79 | 0.852 | - |
| **H2** | 522 | 411 | 10.55 | 0.852 | - |
| **H3** | 544 | 422 | 12.56 | 0.852 | - |
| **H4** | 500 | 339 | 14.77 | 0.852 | - |
| **H5** | 472 | 339 | 17.73 | 0.852 | - |
| **C1** | 355 | 450 | 17.28 | 0.852 | - |
| **C2** | 366 | 478 | 13.90 | 0.852 | - |
| **C3** | 311 | 494 | 8.44 | 0.852 | - |
| **C4** | 333 | 433 | 7.62 | 0.852 | - |
| **C5** | 389 | 495 | 6.08 | 0.852 | - |
| **S1** | 509 | 509 | - | 1.136 | 37.64 |
| **W1** | 311 | 355 | - | 0.852 | 18.12 |

Heat exchanger ($ per year), $145.63a^{0.6}$

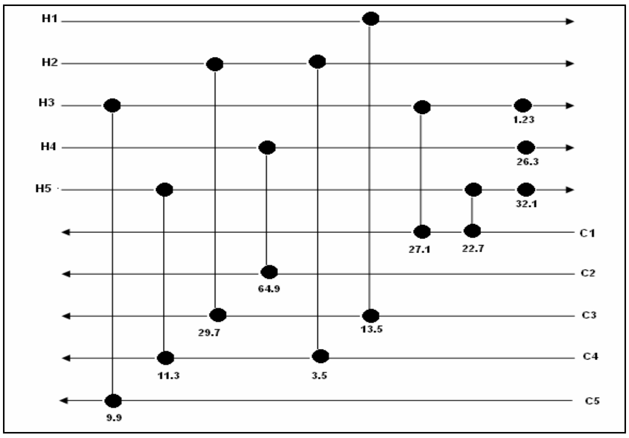


Fig. 6 The final optimal network of case study D

## 5 Conclusion

This paper has presented a novel approach for the synthesis of heat exchanger networks relying on a genetic algorithm to perform structural and parametric optimization. The optimizer determines the exchangers in the final network and computes the optimum stream split flows and heat exchanger duties, for a given HEN structure. The algorithm can support the inclusion of undesirable or forbidden matches, and the enforcement of desirable ones. The newly developed optimization environment allows the user to treat arbitrary flowsheets including structure and parameterization of the system in question simultaneously in the optimization procedure. The simulations and the cost calculations exploit the complete process modeling accuracy without the necessity of simplifications due to restrictions imposed by the optimization method.

The given results demonstrate the suitability of genetic algorithms for HEN optimization. Although the proposed procedure improved greatly the performance of the synthesis, the computational requirements are still a major issue when using superstructures. So it might be beneficial for future works to use a non-superstructure based framework coupled with suggested algorithm.

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