COMSOL and MATLAB® Integration to Optimize Heat Exchangers Using Genetic Algorithms Technique

Juan S. Muñoz[1], Raúl Valencia[2] and Cesar Nieto[*, 3]
[1] Semillero Termodinámica y Fluidos, [2] Grupo Automática y Diseño, [3] Instituto de Energía y Termodinámica.
Facultad de Ingeniería Mecánica. Universidad Pontificia Bolivariana. Colombia.
* Corresponding Author: Universidad Pontificia Bolivariana. cesar.nieto@upb.edu.co

Abstract:

Mathematical models, graphical analysis and numerical solvers allowed us to study heat transfer theory with interesting results. An optimal fin design and optimization process to get an efficient heat exchanger will be presented in this paper. Genetic algorithms technique and finite elements method worked together to find the best geometric configuration for both problems. We designed our own genetic algorithm code named GA7 and adapted it to each optimization problem. Efficiencies below 60% are not economically accepted and must be avoided for fin design. Analysis permitted us to get efficiencies up to 90%. For heat exchanger we could maximize heat flux obtaining different geometric dimension with good results. MatLab® and COMSOL integration increases capacity of GA and offers a new optimization process for COMSOL. This is a great solution for functions of high level of sophistication on energetic systems.

Keywords: Genetic algorithms, geometric optimization, heat exchangers, fins.

1. Introduction

Behavior prediction of physical phenomena is of interest to improve different systems and devices frequently used in engineering applications. For that purpose different methods have been used, i.e. numerical, experimental and analytic approaches. The selection of the method depends on the complexity of the problem to study. Analytic studies are normally used as initial step in any development or optimization methodology. It has the advantage to conduce to initial prediction of simplified phenomena, but has the difficult to extend to more complex situations and systems (i.e. geometry, physical behavior, operation conditions, among others). Experimental approaches have always been the preferred strategies for the study and develop of new technologies, designs and methodologies, due to the option to probe the real phenomena or system to be improved or designed. Energy and time wastefulness and higher costs are some backwards of experimental studies.

Numerical approach has taken advantage of computers development. The application of this approach has conducted to improve several kind of systems, process and devices. Numerical approaches primary consist in the solution of governing equations by means of any numerical or discratization method available for that goal (e.g. Finite Element Method (FEM), Finite Volume Method (FVM), Boundary Element Method (BEM), Meshless Methods). Values for primary variables (i.e. pressure, velocity and temperature), are obtained through governing equations solution and then derivate results (e.g. tangential strain stress, heat flux, mass flux, etc.) are used to establish system performance. Higher complex problems can be studied compared to analytic approaches, although computational efforts increase as well system complexity increase.

Besides, the improvement of systems, time, raw materials, costs and energy has always been the aim of engineers, economist, industrialist, among others. Deterministic and hierarchical schemes had been committed to do that work (e.g. Combinatorial methods, Derivative-free methods, First order methods, Second-order methods, Gradient descent, Newton's method, Quasi-Newton methods, Conjugate gradient method, Hill climbing, Simulated annealing, Evolution strategy, Stochastic tunneling, Differential evolution).

Genetic Algorithms (GA) have proved to be a complete and effective approach for solving optimization problems. GA has been used for the optimization of economy and logistic problems, including timetable and scheduling problems [1]. They are also used in engineering problems for the optimization of geometries, configurations, process feed up, reduction in capital an operational costs, among others [2,3]. GA application is based on the principles of genetics and natural selection to optimize functions and provide a matrix with complete information about the variables evaluated in functions. Conventional optimization methods, quickly find the maximum of an objective function, but they cannot identify difference between local and global maximum (or minimum). GA optimizes functions with extremely complex cost surfaces, jumping out of a local optimal solution and finding the global optimal (maximum or minimum) value of evaluation function (fitness function).

This article presents the integration between numerical solution software based on FEM with a GA optimization tool coded in MATLAB®. The GA optimization tool was initially developed for the optimization of solar collectors [4], with a graphic interface that uses genetic algorithms as search engine. Pseudo numerical models [5] were used for solar collector evaluations with GA and results for geometric variables were obtained under different operation conditions (e.g. incident radiation, room temperature, atmospheric pressure, among others).

Looking for other applications of the optimization engine, we consider the study of more complex fitness functions to improve thermodynamic and fluid systems. Since COMSOL has a programming structure based in MATLAB®, it considers to use it with GA7 (the name of the optimization software developed) for the optimization of two thermal systems: a constant area fin in 2D and a concentric heat exchanger in 2D. While GA MATLAB® code seeks the best solution in population for both fin and heat exchanger, COMSOL solves the governing equations (i.e. continuity, momentum and energy conservation models) using FEM; then, results are employed for fitness function evaluation and selection of better individuals. Developed connection evaluates fitness functions with high precision for thermodynamic systems design with maximum efficiency and lowest costs.

2. Genetic algorithms

Genetic algorithms are a group search techniques for problems optimization. The techniques based on calculation, generally have a group of initials conditions for the solution of the optimization problem. The indirect methods generally look for a local extreme by means of the solution of a group of non linear equations, where the gradient of the objective function becomes similar to zero. The direct methods look for an extreme through a search in the space and it evaluates the gradient in a new point [6].

The numerical technique looks for each point related with the space domain of the objective function, one at the same time. They are easy to implement but require enough computational resources. The techniques of aleatory search (Guided random search techniques) are similar to the previous ones, but have additional information that allows them to solve complex problems. They are divided in simulations and in evolutionary algorithms. The first ones use thermodynamic evolution processes to find the minimum energy states. The evolutionary algorithms are based on the natural principles of selection where each generation is improved through some similar operators to the biological processes. In this category we find the genetic algorithms (GA). Actually, exist several variations regarding the original pattern; a common characteristic is the population handling.

The Genetic Algorithms are adaptive methods that can be used to solve search problems and optimization [6]. It is a technique that emulates theories of biological evolution, as the postulates of Darwin for the natural selection and the survival of the strongest. These theories start from an initial population, apply a series of operators where the best survive, to generate descending that inherit the best characteristics. The stages of a simple cycle in GA are:

- An initial population creation.
- Evaluation of each chromosome.
- Selection of the best.
- Genetic manipulation for the creation of a new population of chromosomes.

In comparison with conventional methods of optimization, the genetic algorithms offer the following advantages [7]:

- Optimization of continuous functions.
- They do not required technical of derivation.
- Optimization of functions with many local

maxima and minima.

- It works with randomly data generated.
- It works successfully in parallel computational systems.
- Hybrid processes of optimization can be generated with the algorithms.

Some of the more usual genetic operators are presented below [1]:

- Selection: this operator chooses among the population chromosomes, the most compatible and the most capable to reproduce for producing an offspring.
- Cross: this operator takes parts of chromosomes imitating to the gametes like in the biological mechanisms.
- Mutation: this operator changes aleatorily the values of some chromosomes.
- Inverse: it inverses the sort of a contiguous section of a chromosome, changing the sort in that the genes are stored.

It is possible to improve the genetic algorithm, if it is also coupled to a local optimizer, generating a hybrid genetic algorithm [7] that combines the power of the GA with the speed of a local optimizer. The GA finds the region of the optimum, and the local optimizer takes over to find the best solution.

3. COMSOL and GA integration

Optimization Lab from COMSOL is an excellent solution for optimal cases. It works iteratively to find a maximum cost for objective functions. Based on differentiable process, COMSOL application solves the equations and interprets solutions. Optimization Lab is able to solve the following kinds of functions: Linear, Quadratic, and Non linear.

GA techniques have several advantages over differentiable base optimization algorithms. GA does not require derivative information, can jump out of a local minimum, and works with numerically generated data, experimental data or analytical functions. Is also well suited for parallel computers, and provides a list of optimum variables for the same objective function. This justifies the use of GA for the optimization of engineering and its integration with a numerical solver like COMSOL. The integration of both numerical tools is initially probed with simplified 2D problem. The first one is a 2D fin, which initially is considered of constant area, but through GA evolution it transform in variable area fin. Energy equation for solids is solved with COMSOL Heat Transfer Steady State Multiphysics model. Then, a 2D counter flow heat exchanger simplified model is analyzed. For this case, the Navier-Stokes equation and the Energy equation are solved by COMSOL Multiphysics solvers. Figure 1 shows the general structure of the interaction between COMSOL and GA codes.

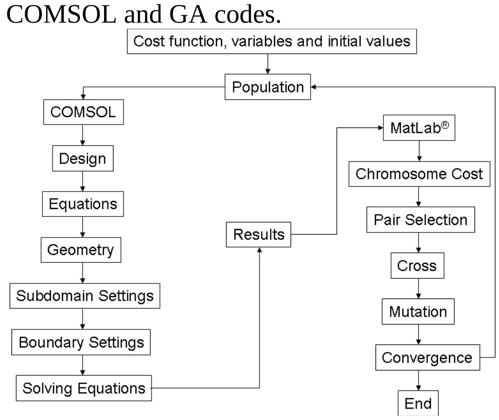


Figure 1. Optimization process

Once we have completed code integration for both programs, we plotted each result and got the evolution of the variables while GA was seeking the best solution. Initially we obtained efficient values around 60% for fin design, with low level of optimization and few iterations. For more iterations and exhaustive design on selection and mutation process we increased the efficient to 95% approximately. Next section exposes mathematical models and fitness functions used in this study. Finally, the results obtained during the application of those models are presented, for both fins and heat exchanger optimized geometries.

4. Mathematical models

Heat transfer module from COMSOL Multiphysics was used to estimate velocity, pressure and temperature fields for different thermal systems analyzed. The General Heat Transfer equation (energy equation) for solids was employed first to study heat flux and temperature distribution in 2D fins. Results from these simulations were used with GA7 optimization software to improve fins thermal efficiency. Results for optimized fins were validated through comparison with analytic results reported by peers. Variations in height and length of fin were imposed to define the different individuals to be analyzed through GA7 and COMSOL interaction. Constant temperature and convective heat flux boundary conditions are defined to solve energy equation into solid fin.

Fluid Thermal Interaction module from COMSOL was employed to solve continuity, Navier-Stokes and energy equation for non isothermal fluid flow into a concentric heat exchanger. Results for temperature distribution and pressure drop are used to estimate thermal efficiency for this system. Variation in heat exchanger diameters and length are also considered to analyze a widely variation of configurations. Constant mass flow and temperature are defined as inlet fluids boundary conditions to the heat exchanger. Gauge pressure equals to zero is imposed at outlet flow boundaries of the heat exchanger. Heat transfer interactions between cold and hot side of heat exchanger is activated. Heat flux equal zero is imposed to external boundaries.

5. Fitness functions

For systems optimization mentioned above, the fitness function to estimate its behavior was selected according to the phenomena present in each system.

5.1 Fin fitness function

For the fin optimization, the fin efficiency was employed as fitness function. The fin efficiency is defined as [8]:

$$\eta_{fin} = \frac{Q_{fin}}{Q_{fin,max}}$$

Where Q_{fin} is the actual heat transfer rate from the fin, and $Q_{fin,max}$ is the maximum or ideal heat transfer rate from the fin if the entire fin were at base temperature. Both heats are function of fin's geometry (i.e. height and length, or fin perimeter and shape), which in fact are the cromosome entries for each individual to be evaluated by GA optimization tool. The actual heat transfer rate from fin is evaluated in COMSOL, by changing the dimensions of fin, selected by genetic operators. The efficiency value (cost value) is evaluated over all population for several generations, until the best individual is selected.

5.2 Heat exchanger fitness function

For the heat exchanger case, the heat flow for hot to cold side is maximized. The heat flow is evaluated in COMSOL by means of subdomain integration tool. This allows the estimation of heat flows for geometries proposed by genetic operators. The inlet and outlet ratios for both streams are used as chromosomes for GA individuals' definition. Material's duct thickness and heat exchanger length are also used to identify individuals during optimization. At the end, the best individual (i.e. heat exchager with higher heat rate exchange) is selected.

6. Results and discussion

Below, results for fin and heat exchanger optimization are presented. Several cases were evaluated as function of geometry variations and operational conditions.

6.1 Fins optimization

The convective removal of heat from surface can be improved if we put extensions on that surface to increase its area. These extensions can take a variety of forms. Bellow we present an analysis of fin optimization to find better applications in heat exchanger design. Fins are commonly used when the convective heat transfer coefficient h_c, is low, cases such as air under natural conditions.

Our objective was to find the best geometric configuration for a fin and analyze heat flow and efficiency of fins. We defined two original codes on COMSOL Multiphysics. The first one creates a curved fin with a maximum efficient of 70% and limited geometric variation. Figure 2 shows the surface of the fin. After that we decided to create a new fin with different parameters to change its length, four different widths and optimize its heat flow through the geometry. Figure 3 illustrates the image of new fin. Boundary condition values are presented in Table 1.

Table 1. Boundary conditions for fin analysis

Variable	Magnitude	Units
Convective coefficient	30	W/m^2k
External temperature	400	K
Boundary temperature	290	K

The first geometric design present excellent solutions but wasn't possible to modify much parameters in its geometry. Figure 4 shows evolution of the efficiency over iterations.

Comparison between Figure 4.a and Figure 4.b, permit us to conclude that iteration process is better for the second design, because each calculation offers a bigger increase for the optimal geometric dimensions. Figure 4 shows that iteration process is better for the second design, because each calculation offers a bigger increase for the optimal geometric dimensions.

In Table 2 iteration (generation evaluated) effect for final efficiency is presented. The optimization search quality was improved through more iteration. However fastest analysis showed good answers.

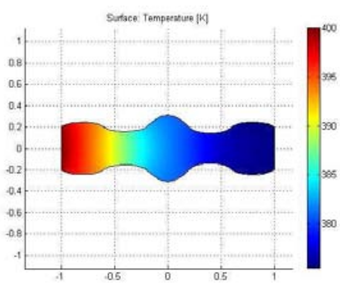


Figure 2. First geometric design in fin analysis

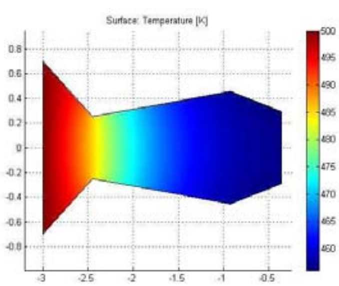
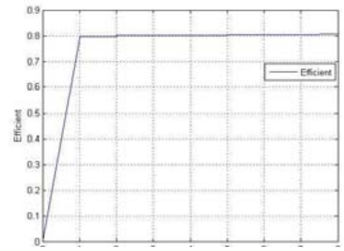


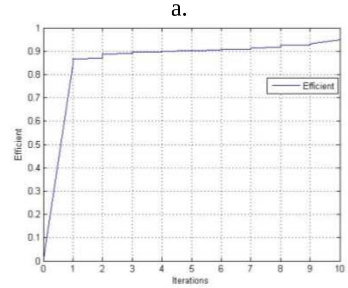
Figure 3. Second geometric design in fin analysis

Theory explains that an infinite length with constant heat flow through geometry has the best value for efficient, however practical design does not permit to construct this kind of surfaces. Once we run the code for analysis length effects we found that the maximum optimal size is controlled by the optimal area permitted to increase the efficiency.

Table 5 is presented fin length effect over final efficiency and temperature distribution. Results are according to fins theory, where fin length is increased while efficiency decreases, because fin temperature decrease [9]. Moreover, as fin length increase the fin tip exposed area tends to reduce, due to heat transfer rate reduction associated with temperature decrease.



a.



b.

Figure 4. Efficient vs. iteration for designs: a. first design; b. second design.

Table 2. Iteration effects on final results.

Iterations or generations	Efficiency
3	0.9431
5	0.9393
8	0.9397
10	0.9537
20	0.9516
30	0.9625

Usually the objective is to minimize the amount of material in fins with the aim of require minimal construction cost. Table 3 shows results for minimization of Area/efficient relation. For more iterations the efficient increases and cost reduces. Figure 5 has graphical results for this analysis.

6.2 Heat exchanger

A great variety of heat exchangers are used in industry process. Geometric dimension, type of heat transfer surface and materials all change according to design requirements. We studied a Two-stream counter flow heat exchanger and designed a MatLab code to optimize geometric values in order to get the maximum efficient. Boundary conditions used for numerical solution with COMSOL as follows (see Table 4).

The typical problem that any heat exchanger solves is getting energy from one fluid to another. Heat flux must be maximized to transport as much energy as possible through the heat exchanger geometry. MatLab and COMSOL integration seeks the best geometric dimensions to optimize flux in two-stream counter flow heat exchanger. Pressure, velocity and temperature (then heat transfer rate) are modified while geometric configuration is changed. Efficiency should be improved to get a better solution.

Table 3. Cost minimization through iteration. (Price for first September week) (3.13US$/pound)

Area/Efficient	Efficiency	Iterations	Cost(US$)
6.2116e-004	0.8049	10	38
5.8531e-004	0.8136	15	36
5.7200e-004	0.8325	20	35

Table 4. Initial values for heat exchanger analysis

Variable	Magnitude	Units
Cold Temperature	330	k
Hot Temperature	660	K
Cold velocity	0.5	m/s
Hot velocity	0.25	m/s
Outlet Pressure	0	Pa

Table 5. Effects of fin length on final results

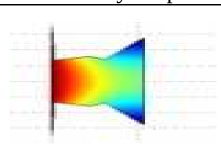
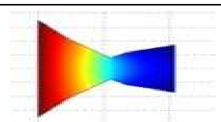
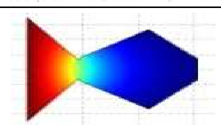
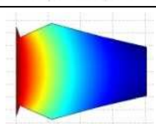
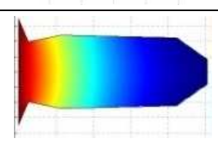
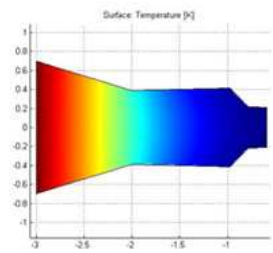
Geometry shape	Length (m)	Efficiency
	1	0.99
	2	0.9834
	3	0.9640
	4	0.9452
	5	0.9082

Table 6. Results for heat exchanger optimization

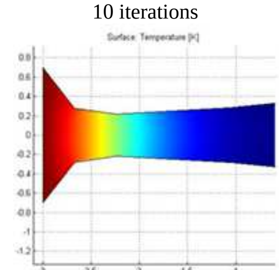
Hot flow entrance (m)	Hot flow exit (m)	Tube width (m)
0.4262	0.4703	0.4515
Cold flow entrance (m)	**Cold flow exit(m)**	**Heat flux (W)**
0.4175	0.3847	674.5330

Figure 6 and Table 6 present results for maximum heat flux heat exchanger configuration. From results is possible to note that hot side outlet is greater than inlet, conducing necessarily to velocity reduction and then an increase in heat transfer residence time, which conduce to raise the heat transfer rate. The cold side is not affected in the same way, since the analysis is conducted for counter flow heat exchanger, thus cold inlet side is greater than outlet.

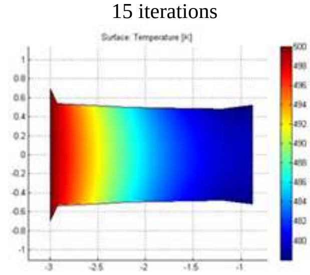
As was defined in fin analysis length effects could affects efficient search. The following information (see Figure 7) shows results for geometric optimization in order to get an optimal heat exchanger length. The same effect over hot outlet and cold inlet is presented. The heat exchanger length changed to improve heat transfer rate and then heat exchanger efficiency.



10 iterations



15 iterations



20 iterations

Figure 5. Cost minimization through iteration.

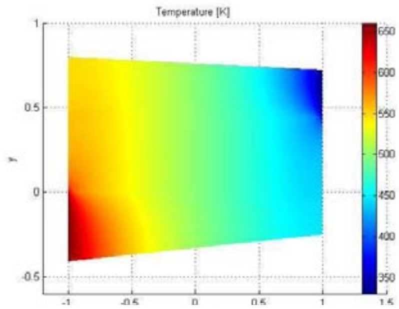


Figure 6. Best geometric configuration for maximum heat flux.

7. Conclusions

COMSOL Multiphysics and GA optimization software integration is a great solution for function of high level of sophistication. Union between finite elements method and genetic algorithm technique increase the use of COMSOL and provide a new option to optimize engineering systems. The interface and the sequence of the code allow us to use it in different applications such finance optimization, optimal mechanical designs and logistical procedures with low costs. GA7 and COMSOL integration provide a powerful tool to identify different solutions for optimal systems. Optimization of thermodynamics systems like heat exchangers and fins, provides us the start of use both simulation tools for analysis of other more complex systems.

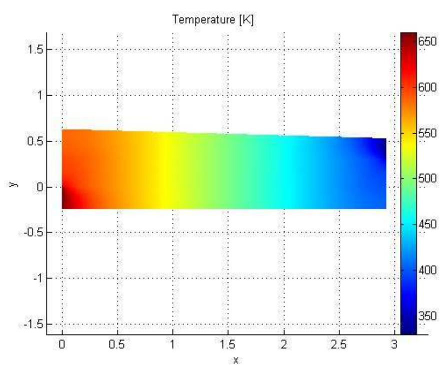


Figure 7. Length effect over heat exchanger configuration

Optimal design of a heat exchanger is not just minimization of pressure difference as much as possible. Efficiency can be augmented by employing extended surfaces around heat exchanger geometry. Adding fins will increase pressure drop, but it will reduce construction cost by increasing overall heat transfer coefficient and reducing required area. Pumping cost, heat transfer, minimal area and fastest solution should be considered in the optimization of efficiency and effectiveness of heat exchanger. Next works includes 3D geometries and other phenomena like chemical reactions in applications such as fuel cells and microheat exchangers and micro mixers.

8. References

1. Goldberg, David E, The Design of Innovation: Lessons from and for Competent Genetic Algorithms, Addison-Wesley, Reading, (2002).
2. B.V. Babu and Vivek. N, Genetic algorithms for estimating heat transfer parameters in trickle bed reactors. Available on line: http://bvbabu.50megs.com.
3. K Nandakumar, Yiqiang Shu, K T Chuang, Predicting geometrical properties of random packed beds from computer simulation, AIChE Journal, **45**, 2286-2297 (1999).
4. Nieto, C.; Muñoz, J.; Del Rio, S.; Valencia, R.; Toro, M., Diseño de colectores solares por medio de algoritmos genéticos, III Congreso Internacional Sobre Uso Racional y Eficiente de la Energía – CIUREE (2008)
5. Duffi, J, Solar engineering of thermal processes. Third edition. 944 pp (1991)
6. Ribeiro, Jose and Treleaven, Philip, Genetic Algorithm Programming Environments, London: University College (1994).
7. Haupt, Sue and Haupt, Randy, Practical Genetic Algorithms, Wiley-Interscience, pp. 253 (2004).
8. Yunus A. Ç., Heat Transfer: A Practical Approach, McGraw-Hill, 2d. Edition (2003)
9. Lienhard, J., A Heat Transfer Textbook. Phlogistion Press. Cambridge Massachusetts. Third edition. 2005.

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