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APPLICATION OF GENETIC, GRADIENT, AND HYBRID OPTIMIZATION STRATEGIES TO A REFERENCE COGENERATION SYSTEM: A COMPARATIVE STUDY

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Abstract. *The thermoeconomic optimization and improvement of energy systems is an engineering area of intense recent research. Many different methodologies have been developed, however the need for more efficient techniques remains. Genetic algorithms are relatively easy to code and robust, i.e., will less likely stop at local optima, but they tend to be computationally expensive. Gradient methods are effective optimization strategies, however they require the calculation of derivatives, which is not always possible. Hybrid methods, on the other hand, attempt to combine the efficiency of gradient methods with the robustness of genetic algorithms. In this paper we present the implementation of three different approaches for the mathematical optimization of a reference cogeneration system. The first strategy is based on genetic operators. The second strategy is the BFGS (Broyden-Fletcher-Goldfarb-Shanno) gradient method. The third method is hybrid, and is a combination of the previous two strategies. The coded algorithms are applied to the benchmark CGAM cogeneration problem. A comparative analysis of the generated results reveals the advantages and disadvantages of each method, and sheds light on the issue of the selection of algorithms to be used in the optimization and improvement of energy systems.*

Keywords. *genetic operators, gradient methods, hybrid methods, optimization, energy systems.*

1. Introduction

Modern design of energy systems must consider efficient utilization of natural energy resources, reduced harms to the environment, and sustainable development (Rosen and Dincer, 2001). A large number of techniques for energy systems design optimization have been developed worldwide in the past two decades (Tsatsaronis, 1993; Donatelli, 2002; Vieira, 2003; Frangopoulos, 2003). The field of exergoeconomics (Lozano and Valero, 1993; Bejan et al., 1996) can address environmental issues, reveal the cost formation process of system products, and aid system optimization. In Brazil, research in exergoeconomics has been done on the evaluation and interpretation of different cost partition methodologies (e.g., Antunes and Silveira, 1999; Balestieri et al., 1999; Cerqueira and Nebra, 1999; Donatelli et al., 2000; Gallo and Gomes, 2003; Júnior and Arriola, 2003), and on exergoeconomic optimization techniques (e.g., Donatelli, 2002; Vieira, 2003; Ferreira and Balestieri, 2003; Colombo et al., 2004; Vieira et al., 2004, 2005, 2006). To evaluate and compare different exergoeconomic methodologies, *C*. Frangopoulos, *G*. Tsatsaronis, *A*. Valero, and *M*. von Spakovsky have proposed the optimization of the *CGAM* five-component cogeneration system as a benchmark problem (Tsatsaronis, 1994), which gained wide acceptance thereafter.

On the one hand, it is a fact that exergoeconomics provides insights to system optimization (Bejan et al., 1996). On the other hand, to actually perform exact system optimization, the application of a mathematical optimization technique is ultimately required. An optimization procedure can be carried out by formulating the optimization problem for the thermal system with the thermodynamic balance equations and the component model equations as constraints (Jaluria, 1998; Arora, 2004). Furthermore, these equations must be explicit, and the involved variables must be treated together with the decision variables, thus significantly increasing the dimension of the problem. Recently, Vieira et al. (2004, 2005, 2006) developed techniques which integrate optimization algorithms with a process simulator, such that the thermodynamic constraints are dealt with by the program. In any case, a carefully selected optimization algorithm should be employed, such that the whole optimization task is accomplished efficiently. In fact, even for dealing with the relatively simple CGAM cogeneration system, tens of variables are required; note that the number of variables rapidly increases as the system becomes more complex, as in real energy production systems.

To aid the selection of an efficient optimization method applicable to an energy system, in this paper we effect a comparative study with three different approaches: genetic, gradient, and hybrid (Padilha, 2006). Genetic algorithms are relatively easy to code and robust, i.e., will less likely stop at local optima, but they tend to be computationally expensive. Gradient methods are effective optimization techniques, however they require the calculation of derivatives, which is not always possible, and they are strongly dependent on the initial guess, mainly when the problem has many local optima, as energy systems. Hybrid methods, on the other hand, attempt to combine the efficiency of gradient methods with the robustness of genetic algorithms. Here, specifically, we present the implementation of three different approaches for the mathematical optimization of a reference cogeneration system. The first approach is based on genetic operators. The second approach is the BFGS (Broyden-Fletcher-Goldfarb-Shanno) gradient method. The third approach is hybrid, and is a combination of the previous two methods. The coded algorithms are applied to the benchmark CGAM cogeneration problem. A comparative analysis of the generated results reveals the advantages and disadvantages of each method, and sheds light on the issue of the selection of algorithms to be used in the optimization and improvement of energy systems (Vieira, 2003; Vieira et al., 2004, 2005, 2006).

2. The CGAM Problem

As noted in the Introduction, in this paper we apply three different optimization methods to solve the benchmark CGAM problem (Tsatsaronis, 1994). The problem consists in the optimization of a reference cogeneration system, for which the thermodynamic, physical, and economic models are given. The equations of the thermodynamic and physical models are well-known, and are given in detail by Tsatsaronis (1994) and Vieira (2003); therefore, they will not be repeated here. Such equations, together with the system physical limits, represent the equality and inequality restrictions of the optimization problem. The CGAM problem, though small-scale, is typical of energy systems optimization, in that it is nonlinear, and has an objective function which does not behave smoothly over all the design domain.

The CGAM system, shown in Figure 1, is a cogeneration system that produces fixed amounts of electrical power and saturated steam. The electricity production is 30 MW, and the saturated steam mass flow rate at 20 bar is 14 kg/s. The CGAM system consists of the following 5 components: air compressor, air preheater, combustor, gas turbine, and heat recovery steam generator (HRSG). The combustor fuel is natural gas with a lower heating value of 50000 kJ/kg.

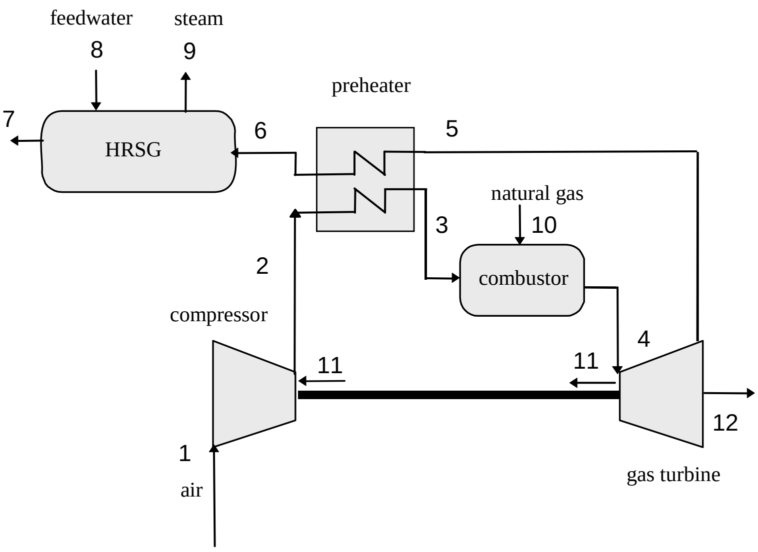

Figure 1. The CGAM cogeneration system (HRSG is the heat recovery steam generator).

The selected decision variables for the optimization problem are the air compressor pressure ratio, R_c, the compressor and turbine isentropic efficiencies, respectively η_{AC} and η_{GT}, the temperature of the air at the inlet to the combustion chamber, T_3, and the temperature of the combustion gases at the inlet to the gas turbine, T_4. The restrictions on (i.e., the ranges which establish the limiting values for) the decision variables are: $7 \le R_c \le 27$; $0.7 \le \eta_{AC} \le 0.9$; $0.7 \le \eta_{GT} \le 0.9$; 700 K $\le T_3 \le$ 1100 K; 1100 K $\le T_4 \le$ 1500 K.

To evaluate costs of an energy system, one should consider the capital investment cost, the operation and maintenance costs, and the fuel cost. For the CGAM problem, because it serves as a reference for comparison of different optimization methodologies, a simplified economic model is assumed, based on the capital recovery factor, *CRF* (Tsatsaronis, 1994; Bejan et al., 1996). In this model, the total capital investment, *TCI* ($), of a system is given by the sum of all the purchased-equipment costs, *PEC* ($), of the components of the system multiplied by a factor β, as given by

$$TCI = \sum_k TCI_k = \sum_k \beta\ PEC_k = \beta \sum_k PEC_k = \beta\ PEC\ , \tag{1}$$

where $k = 1,\ldots,NK$ denotes the k^{th} component, and NK is the total number of system components. The purchased-equipment cost of each component of the CGAM system is shown in Table (1). The symbols $\dot{m}_a$, $\dot{m}_g$ and $\dot{m}_s$ (kg/s) represent, respectively, the air, combustion products, and steam mass flow rates, U (kW/(m^2·K)) is the overall heat transfer coefficient, $LMTD$ (K) is the log mean temperature difference, and $\dot{Q}$ (kW) is the heat transfer rate.

Table 1. Equations for the purchased-equipment costs of the components of the CGAM system.

Compressor (AC)	$PEC_{\text{AC}} = \left(\frac{39.5\dot{m}_a}{0.90-\eta_{\text{AC}}}\right)\left(\frac{P_2}{P_1}\right)\ln\left(\frac{P_2}{P_1}\right)$
Combustion chamber (CC)	$PEC_{\text{CC}} = \left(\frac{25.6\dot{m}_a}{0.995-\left(P_4/P_3\right)}\right)\left[1+\exp\left(0.018T_4-26.4\right)\right]$
Turbine (GT)	$PEC_{\text{GT}} = \left(\frac{266.3\dot{m}_g}{0.92-\eta_{\text{GT}}}\right)\ln\left(\frac{P_4}{P_5}\right)\left[1+\exp\left(0.036T_4-54.4\right)\right]$
Air preheater (APH)	$PEC_{\text{APH}} = 2290\left(\frac{\dot{m}_g\left(h_5-h_6\right)}{U\left(LMTD\right)}\right)^{0.6}$, $U = 0.018$ kW/(m^2·K)
HRSG (PH – water preheater; EV – evaporator)	$PEC_{\text{HRSG}} = 3650\left[\left(\frac{\dot{Q}_{\text{PH}}}{\left(LMTD\right)_{\text{PH}}}\right)^{0.8}+\left(\frac{\dot{Q}_{\text{EV}}}{\left(LMTD\right)_{\text{EV}}}\right)^{0.8}\right]+11820\dot{m}_s+658\dot{m}_g^{1.2}$

The capital recovery factor, CRF, is given by

$$CRF = \frac{i\left(1+i\right)^l}{\left(1+i\right)^l-1}, \tag{2}$$

where i and l are the interest rate and the useful system life, respectively. The fuel cost rate ($/h) is given by

$$\dot{C}_{\text{F}} = c_{\text{F}}\dot{m}_{\text{F}}LHV, \tag{3}$$

where c_{F} ($/kJ), $\dot{m}_{\text{F}}$ (kg/h) and LHV (kJ/kg) represent, respectively, the specific cost, the mass flow rate and the lower heating value of the fuel.

The total cost rate is the sum, on a rate basis, of the capital investment cost, the operation and maintenance costs, and the fuel cost; in fact, the total cost rate is the objective function, OF ($/h), to be minimized when solving the CGAM problem, and is written as (Tsatsaronis, 1994; Bejan et al., 1996)

$$OF = \sum_{k=1}^{NK}\dot{Z}_k + \dot{C}_{\text{F}} = \frac{\left(\sum_{k=1}^{NK}CRF\left(1+\gamma\right)TCI_k\right)}{\tau} + c_{\text{F}}\dot{m}_{\text{F}}LHV, \tag{4}$$

where τ is the amount of hours that the system operates in one year, and γ is the maintenance factor. The values prescribed for the parameters of the economic model are: $\beta = 1$, i = 12.7%, l = 10 years, $\tau = 8000$ hours and $\gamma = 0.06$.

In Table (2), the optimal values for the decision variables and objective function of the CGAM problem, taken from Tsatsaronis (1994), are shown.

Table 2. Optimal values for the decision variables and objective function of the CGAM problem (Tsatsaronis, 1994).

	R_{c}	η_{AC}	T_3 (K)	η_{GT}	T_4 (K)	OF ($/h)
Optimal value	8.5234	0.8468	914.28	0.8786	1492.63	1303.23

3. The Genetic Algorithm

The mathematical optimization methods that are based on the ideas of populational genetic evolution are derived from the seminal work by John Holland, who published the book "Adaptation in Natural and Artificial Systems" in 1975 (Holland, 1975). Since then, many variants of the original idea have been studied and applied successfully to different areas of knowledge. Generally, methods which attempt to mimic biological mechanisms are termed evolutionary methods.

In the genetic algorithm – GA – that we implement (Padilha, 2006), each iteration (generation) works with a set of possible solutions to the problem at hand, here the CGAM problem. Each of these solutions (individuals) have been real-coded in a vector (chromosome) composed by the five decision variables (genes) of the problem: R_c, T_3, T_4, η_{GT}, and η_{AC}. Each individual is associated with a fitness (aptitude) value, which for the CGAM problem corresponds to the value of the objective function (total cost rate, $/h). In this manner, the individuals who are best fit in a population are the ones, who possess the lower values of the total cost rate; thus, after the evolution of some generations, at the end of the optimization process, the fittest individual constitutes the problem optimal solution.

The basic idea of the current algorithm is represented in Figure 2. Initially, a population is generated randomically. Next, the selection operator chooses, arbitrarily and not considering their fitness, two individuals of the population, who are designated as potential parents, i.e., who will possibly mate.

A real number in the interval [0,1) is then drawn from a uniform probability density function, so as to verify whether or not the mating of the potential parents will occur. If the number falls outside the range for crossover, defined through an input probability of occurrence of a crossover, the parents will pass directly on to the new population without any alteration. In the opposite case, the crossover operator is applied to generate two descendants or children. The crossover operator consists in a combination of genes (decision variables) of the parents passing on to the descendants. The main objective of the occurrence of crossover is to promote the evolution of the population, leading to individuals who are more fit, and to munition the optimization procedure with a certain degree of convergence.

After the action of the crossover operator, another real number in the interval [0,1) is drawn from a uniform probability density function, this time to verify whether or not an arbitrary alteration in the genetic material of the new individuals of the population will take place. If the number falls inside the range for mutation, defined through an input probability of occurrence of a mutation, the mutation operator is applied. The mutation operator consists in the alteration of some of the genes of the generated descendants, resulting in new individuals different from the original. Mutation introduces diversity in the population, and permits the GA to escape from stagnation pressures. The mutation operator equips the GA with a solution search potential in all of the design domain, thus enabling the algorithm to escape from local minima.

The two fittest individuals among the generated descendants and their parents are then selected as members of the population of the new generation. The algorithm proceeds with the selection-crossover-mutation sequence, promoting the evolution of the population along the generations, until a prescribed stopping criterion is satisfied. The criterion establishes when an individual is found, whose fitness is sufficiently close to the optimum of the objective function.

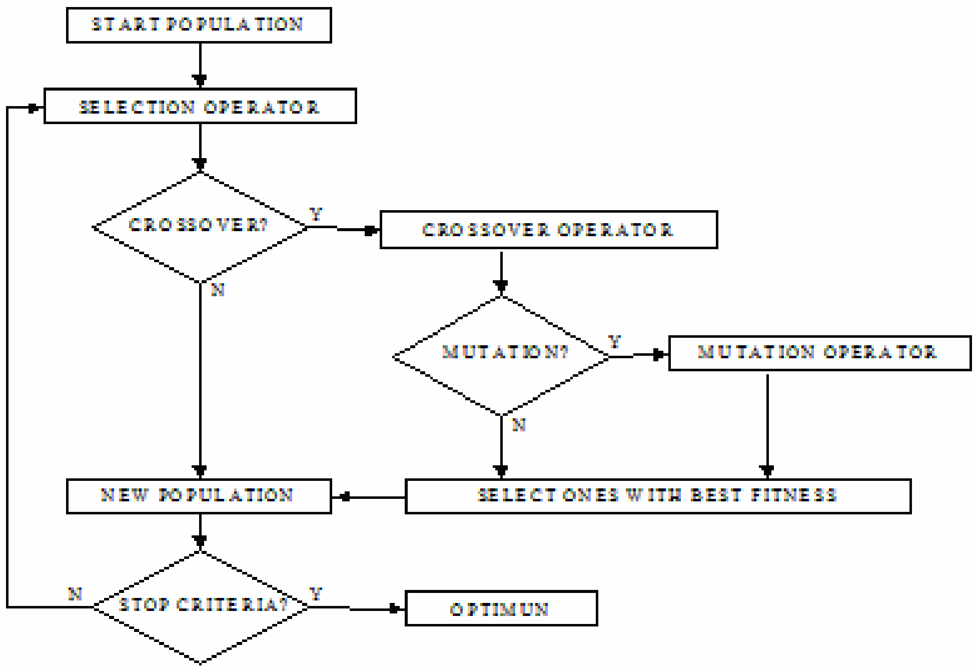

Figure 2. Schematic of the genetic algorithm.

4. The BFGS Gradient Method

The BFGS (Broyden-Fletcher-Goldfarb-Shanno) Method is classified as a quasi-Newton method. These kinds of methods try to calculate the Hessian appearing in the Newton-Raphson method in a manner that does not involve second order derivatives. Usually they employ approximation for the Hessian based only on first order derivatives. Thus, they have a slower convergence rate than the Newton-Raphson method, but they are computationally faster.

As in Colaço et al. (2005, 2006), let us define a new matrix **H**, which is an approximation to the inverse of the Hessian as

$$\mathbf{H}^k \cong \left[\mathbf{D}^2 U(\mathbf{x}^k)\right]^{-1} \tag{5}$$

where $\mathbf{D}^2 U(\mathbf{x})$ is the Hessian (matrix of 2nd order derivatives).

Thus, the quasi-Newton methods follow the general iterative procedure given by (Colaço et al., 2006)

$$\mathbf{x}^{k+1} = \mathbf{x}^k + \alpha^k \mathbf{d}^{k+1} \tag{6}$$

where the direction of descent is given by

$$\mathbf{d}^{k+1} = -\mathbf{H}^k \nabla U\left(\mathbf{x}^k\right) \tag{7}$$

The matrix **H** for the BFGS method is iteratively calculated as (Fox, 1971)

$$\begin{aligned} &\mathbf{H}^k = \mathbf{H}^{k-1} + \mathbf{M}^{k-1} + \mathbf{N}^{k-1} \quad \text{for k = 1,2,…} \\ &\mathbf{H}^k = \mathbf{I} \quad \text{for k = 0} \end{aligned} \tag{8}$$

where **I** is the identity matrix. Note that, for the first iteration, the quasi-Newton method starts as the Steepest Descent method.

Note that, since the matrix **H** is iteratively calculated, some errors can be propagated and, in general, the method needs to be restarted after certain number of iterations (Fox, 1971). Also, for this method, the matrices **M** and **N** are calculated as

$$\mathbf{M}^{k-1} = \left(\frac{1+\left(\mathbf{Y}^{k-1}\right)^T \mathbf{H}^{k-1}\mathbf{Y}^{k-1}}{\left(\mathbf{Y}^{k-1}\right)^T \mathbf{d}^{k-1}}\right)\frac{\mathbf{d}^{k-1}\left(\mathbf{d}^{k-1}\right)^T}{\left(\mathbf{d}^{k-1}\right)^T \mathbf{Y}^{k-1}} \tag{9}$$

$$\mathbf{N}^{k-1} = -\frac{\mathbf{d}^{k-1}\left(\mathbf{Y}^{k-1}\right)^T \mathbf{H}^{k-1} + \mathbf{H}^{k-1}\mathbf{Y}^{k-1}\left(\mathbf{d}^{k-1}\right)^T}{\left(\mathbf{Y}^{k-1}\right)^T \mathbf{d}^{k-1}} \tag{10}$$

Figure 3 shows schematically the iterative procedure for the BFGS optimization method (Colaço et al., 2006).

5. The Hybrid Genetic-BFGS Method

The purpose of the hybrid algorithm of this work (Padilha, 2006) is to couple the robustness of the genetic algorithm, which visits all of the search domain of the problem at hand, with the optimization efficiency of the BFGS gradient method, which has a fast speed of convergence (i.e., a relatively small number of required iterations), and is easy to implement and adjust. The coupling also permits, that the hybrid algorithm looks for optimal solutions (through the BFGS) without getting stuck in local minima (through the GA). Similar works are available in the literature (http://www.ads.tuwien.ac.at/research/HybridOptimization/; see also the discussion and references in Colaço et al., 2005, 2006), however they utilize different hybrid schemes, involving the coupling of various types of evolutionary algorithms with the BFGS and other methods.

The present hybrid strategy consists, first, in the generation of a population, and, next, in the evolution of the population through the GA, as described in section 3 and shown in Figure 2. However, at the end of each generation (iteration), only the standard deviation of the aptitudes (objective function values) of the newly generated population individuals is evaluated. If the standard deviation reaches a prescribed minimum value, the fittest individual (i.e., the one with the best aptitude, or the lowest value for the objective function) of this population is passed on (as an initial guess) to the BFGS method. This condition on the standard deviation indicates that (members of) the population should already be in the vicinity of an optimal value for the objective function, and it is expected that the BFGS engine will reach it with less effort than the GA.

In this way, the fittest individual now serves as an initial point, $\mathbf{x}^0$, for the BFGS method, and the optimization then proceeds as described in section 4 and shown in the diagram of Figure 3. After convergence is reached in the BFGS step, the improved individual returns to the population. Once again, optimization through the GA is (re)initialized, to search for a new region which might contain an individual with a better aptitude than previously encountered. The hybrid algorithm evolves in this manner, commuting back and forth between the GA and the BFGS, until a prescribed stopping criterion is satisfied.

The parameters originally adjusted for the GA and the BFGS schemes are kept for the hybrid method. The new parameters introduced with the hybrid algorithm are the minimum standard deviation of the population aptitude at the end of each generation of the GA, and the maximum number of commutations between the GA and the BFGS. Of course, it is expected that working values for these parameters should vary from problem to problem. For the CGAM problem tackled in this work, the values adopted for the minimum standard deviation and the maximum number of commutations are, respectively, 10^{-3} and 1 (see discussion in Padilha, 2006).

Separate tests conducted to adjust the various parameters indicate that the minimum standard deviation is directly related to the stopping criterion of the search through the GA (Padilha, 2006). Values for the standard deviation of the population aptitude that are too low, induce a large number of generations in the GA before the hybrid method commutes to the BFGS engine. In these cases, it is verified that the BFGS, in general, can only find better values for the aptitude in the first few iterations. By the same token, subsequently, the GA cannot evolve, because the standard deviation of the aptitude is already less than the minimum prescribed. In this case, the commutations between the GA and the BFGS do not have any beneficial effect, they only increase the number of evaluations of the objective function. On the other hand, values for the standard deviation of the population aptitude that are too high, may induce failure of the BFGS engine, because the initial point may lie in a non-smooth region of the search domain. The use of varying values for the standard deviation in the course of the evolution of the hybrid algorithm might be a way to circumvent this problem, i.e., to perform the commutations in an optimal way.

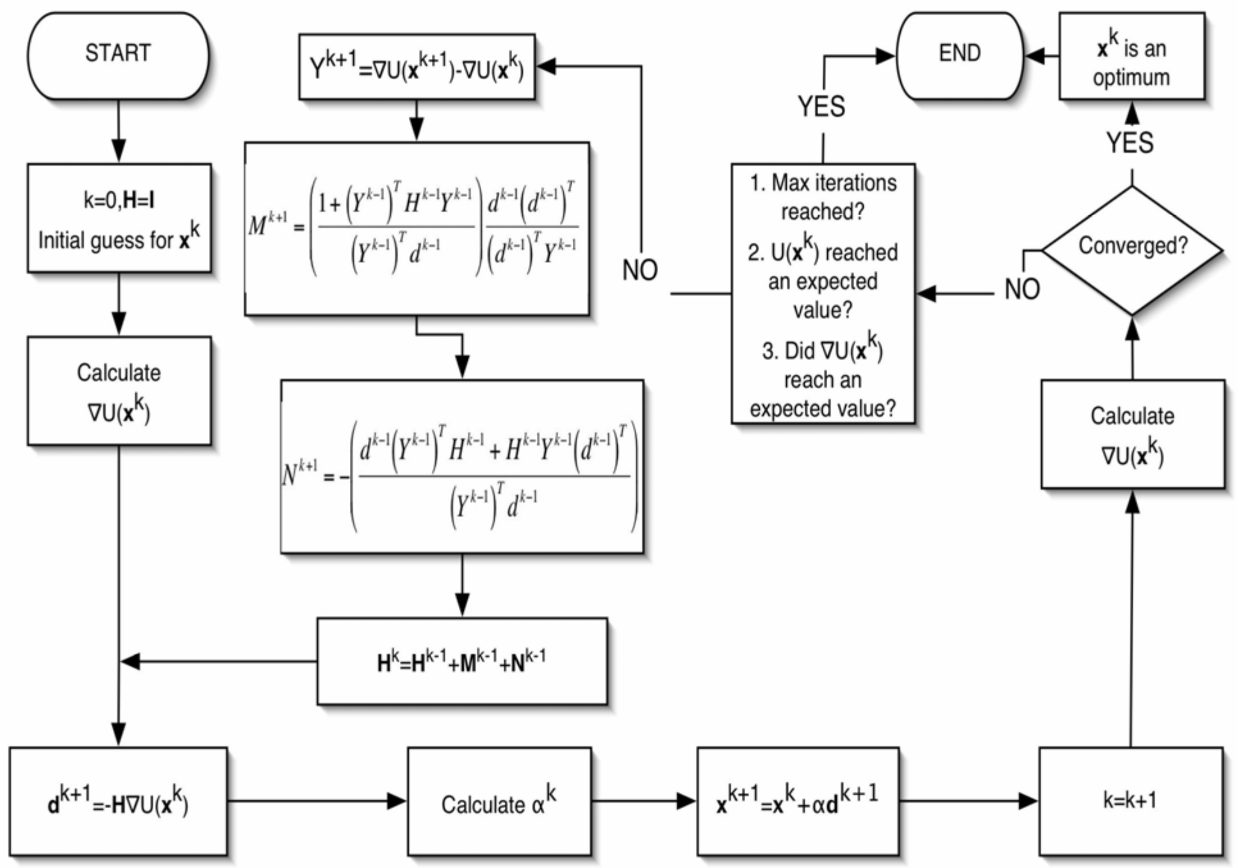

Figure 3. Schematic of the iterative procedure for the BFGS method (Colaço et al., 2006).

6. Results and Analysis

In this section we present, for each of the three different optimization approaches described earlier, the results obtained for the decision variables, objective function, number of iterations, N_{IT}, and number of evaluations of the objective function, N_{OF}, when we solve the CGAM problem. The methods that we employ, genetic, BFGS, and hybrid, are designated as GA, BFGS, and HM, respectively. Our results are presented in Table (3) together with the corresponding reference values, denoted CGAM (Tsatsaronis, 1994), taken from Table (2). For each method, we also present in the table the relative difference δ_{OF}, defined as

$$\delta_{OF} = \frac{\left|OF - OF_{CGAM}\right|}{OF_{CGAM}} \times 100\% \,. \tag{11}$$

In Table (3) we observe that the values obtained for the objective function using the GA and HM approaches essentially coincide with the reference value, being off by no more than a relative difference of 0.037%, which is negligible for engineering purposes. However, the HM is a bit more efficient in terms of number of function evaluations required. Also, the values obtained for the decision variables are generally satisfactory (see discussion in Vieira (2003) and Vieira et al. (2006) regarding deviations in the optimal values of decision variables); the better values are obtained, again, with the GA and HM approaches. The BFGS presents the worst value for the objective funtion, however it is the fastest approach. As expected, the main disadvantage of the GA is the computational time (proportional to N_{OF}), the largest of the three.

In general, it is fair to conclude that the HM and GA approaches lead to satisfactory results, the former having presented itself as the most promising of the three. Because of the high frequency of discontinuities in the domain of the nonlinear CGAM problem, and the likely large number of local minima, the BFGS does not perform well. Thus, the performance of the HM is somewhat contaminated by that of the BFGS. The latter fact, together with the non-optimal commuting scheme, explain the modest improvement of the HM with respect to the GA: 8% less computational effort. Overall, of the three methods, the HM has turned out to be the best, albeit requiring some effort to adjust the control parameters of the two coupled methods (GA and BFGS). It is also expected that the HM can be further improved, by considering different coupling schemes.

Table 3. Results for the CGAM optimization problem using genetic, BFGS, and hybrid methods.

Results \ Methods		GA	BFGS	HM	CGAM
Decision variable	R_c	8.9073	11.9898	8.9073	8.5234
	η_{AC}	0.8454	0.8513	0.8434	0.8468
	T_3 (K)	908.46	877.64	908.46	914.28
	η_{GT}	0.8795	0.8856	0.8802	0.8786
	T_4 (K)	1487.94	1493.02	1487.94	1492.63
OF (\$/h)		1303.67	1322.48	1303.71	1303.23
δ_{OF} (%)		0.034	1.48	0.037	0
Number of *OF* evaluations, N_{OF}		3891	1591	3580	-
Number of iterations, N_{IT}		9	7	9	-

7. Acknowledgements

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