COMPARATIVE ANALYSIS OF COGENERATION POWER PLANTS OPTIMIZATION BY A DIRECT SEARCH AND A STOCHASTIC METHOD USING SUPERSTRUCTURE AND PROCESS SIMULATOR

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Abstract. *Thermal systems are essential in facilities such as thermoelectric plants, cogeneration plants, refrigeration systems and air conditioning, among others, in which much of the energy consumed by humanity is processed. In a world with finite natural sources of fuels and growing energy demand, issues related with thermal systems design, such as cost estimatives, design complexity, environmental protection and optimization are becoming increasingly important. Therefore the need to understand the mechanisms that degrade the energy, improve the energy sources use, reduce environmental impacts and also reduce project, operation and maintenance costs. In recent years has occured a consistent development of procedures and techniques for computational design of thermal systems. And in this context, the fundamental objective of this study is a performance comparative analysis of structural and parametric optimization of a cogeneration system by a direct search method (flexible polyhedra) and a stochastic method (genetic algorithms). This research work uses a superstructure, modeled in a process simulator (IPSEpro of SimTech), in which the appropriate design case studied options are included. Accordingly, the cogeneration system optimal configuration is determined as a consequence of the optimization process, restricted within the configuration options included in the superstructure. The optimization routines are written in the "MSExcel - Visual Basic" to work perfectly coupled with the simulator process. At the end of the optimization process, the system optimal configuration, given the characteristics of each specific problem, should be defined.*
Keywords: *Cogeneration Power Plant; Optimization; Flexible Polyhedra; Genetic Algorithm; Superstructure; Process Simulator; ...*

1. INTRODUCTION

Nowadays, it has become necessary to reduce the use of natural energy resources, especially the non-renewable. The necessary reduction may be partially accomplished by consistent energy use strategies and optimization of the energy conversion processes. A cogeneration plants is an important example of the energy conversion processes. In the design of this plants there are complex interactions between the available components, large number of possible design alternatives and lack of accurate components cost data, that become this task (cogeneration systems design) very complicated.

Several techniques and methods suitable for thermal systems design and optimization has been developed (Boehm, 1997), as process simulators, modeling of superstructures and several mathematical optimization methods. In this context, the major objective is to pursue a performance comparative analysis of a structural and parametric cogeneration system optimization by a direct search method (flexible polyhedra) and a stochastic (genetic algorithm), using a superstructure, modeled in the process simulator environment (IPSEpro of SimTech). The superstructure is modeled in IPSEpro and the optimization algorithms are written in "MSExcel - Visual Basic". The optimization routines are written to work perfectly coupled with the simulator process.

The direct search method (flexible polyhedra) has simple code implementation, without using variables derivatives during optimization, and has precarious performance to attaing optimums in non-linear complex problems. Its poor performance motivated the application of a stochastic method. The genetic algorithm is chosen for its ability to attain optimums even in complex problems characterized as highly non-linear. And for not using variables derivatives during optimization and a rather simple code implementation. Meanwhile, this alghorithm has some hindrances, such as the need to control and eliminate failures in the simulation mostly due to its stochastic search method. Also, depending on the fitness landscape shape, the genetic alghorithm may converge towards local optimum or even arbitrary points rather than the global optimum of the problem. This problem was alleviated by increasing the rate of mutation and enhancing elitism.

The design guidelines, as conceived, aims to hasten cogeneration systems design and to reduce financial expenses. However not excluding the steps that require reasoning and decision make. This latter feature should be stressed as is recommended by El-Sayed and Gaggioli (1989).

2. COGENERATION PLANT

A superstructure was designed in the commercial process simulator software (IPSEpro of SimTech) to represent all envisaged cogeneration plants. The superstructure contains all major project options appropriate to cogeneration power plants. In this way, a cogeneration power plant optimal configuration is obtained through optimization, but obviously restricted within possible alternatives obtainable from the superstructure model. A schematics of the superstructure is presented in Figure 1.

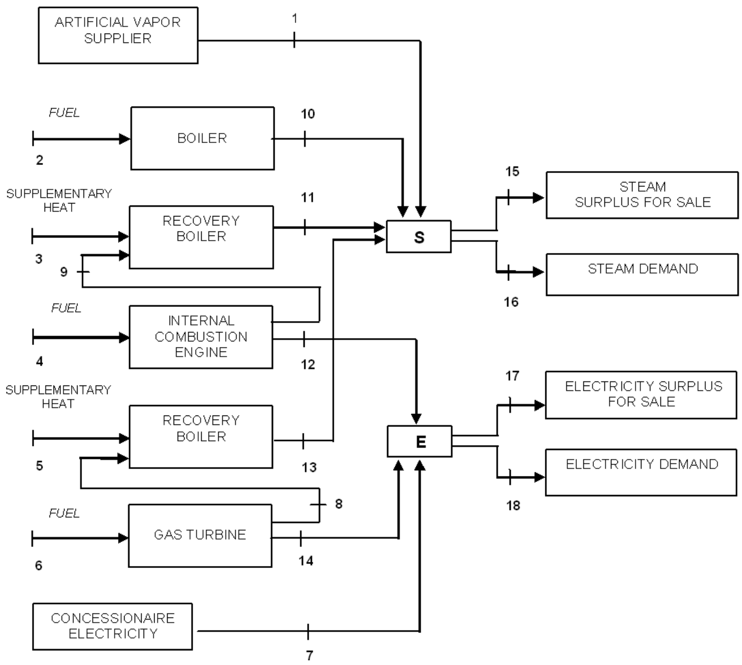

Figure 1. Schematics of the superstructure.

The optimization computer programs are written in MSExcel - Visual Basic and are coupled with the simulation software (IPSEpro). These proposed setting has consistently achieved optimum configurations. Meanwhile, the optimum configurations depends heavily on the specific characteristics of the cogeneration power plant technical, economical, environmental and legislation circumstances. These characteristics, i.e, boundary conditions, have profound impact in the design and the model is robust for changes in premises.

2.1 SUPERSTRUCTURE

A superstructure destined to cogeneration power plants structural and parametric optimization was designed as a large thermal system. As shown in Figure 2 the system model contains several basic alternatives capable of supplying, individually or in association, eletricity and steam according to demand. Thus, it basic usefulness is to guarantee configuration flexibility to be explored in the search for optimum systems, besides providing mass and energy balances for the entire system. Literature provides some successful application of superstrutures for optimization as in Maia et al. (1995), Donatelli (2002) and Koch et al (2007).

The primary triggers considered are a gas turbine and an internal combustion engine, both fueled with natural gas. Natural gas is the only fuel included in the model. The energy utility concessionaire may supply and buy eletrical energy from the cogeneration power plant without imposed limits. Meanwhile, for this specific work, eletrical energy could be offered to the concessionaire without cost, i.e., price set to zero.

There is a requirement for medium and low pressure steam to the superstructure model. The medium pressure steam (saturated at 11 bar) and the low pressure steam (saturated at 1.85 bar) can be provided with the following equipments:

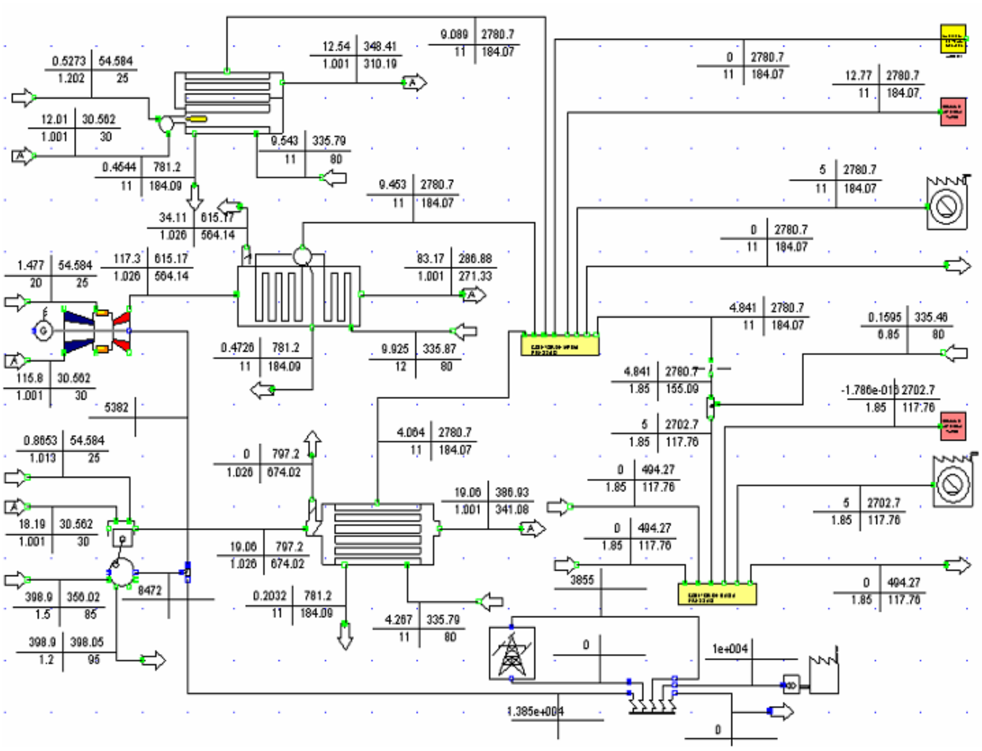

Figure 2. Superstructure as modeled in IPSEpro.

conventional boiler, heat recovery boiler connected with the gas turbine and heat recovery boiler connected with the internal combustion engine. The necessary equilibrium between steam production and demand, during optimization, is guaranteed by artificials steam supplier and consumer. The artificials steam supplier and consumer have the purpose to always ensure a solution to the balance of mass and energy of the superstructure, as used in Donatelli (2002). The low pressure steam is originated by the pressure reduction of medium pressure steam.

3. OPTIMIZATION

The cogeneration system optimization problem, treated in this work, has its mathematical formulation described in Equation 1. For this specific analysis the eletricity and steam demand, weather conditions, eletricity and fuel prices are assumed to be constant with market values.
Minimize:

$$\hat{F}(x, y^+(x,p), p) = F(x, y(x,p), p) + \gamma(y_{art}(x,p))^2 + \theta(x, y(x,p), p))^2. \tag{1}$$

Subject to:
$y^+(x,p) = 0$
$x \in [min, max]$
$x \in \Re^n, \quad y \in \Re^m, \quad p \in \Re^k, \quad y^+ \in \Re^{(m+d)}, \quad y_{art} \in \Re^d, \quad \hat{F}, F, \gamma, \theta \in \Re$
where,
$\hat{F} \rightarrow$ objective function including the terms of penalty;
$F \rightarrow$ objective function;
$x \rightarrow$ Set of decision variables (or project);
$y \rightarrow$ Set of dependent variables, some of the simulator process;
$p \rightarrow$ Set of independent variables treated as parameters;
$g \rightarrow$ Restrictions of inequality;
$n \rightarrow$ Number of decision variables;
$m \rightarrow$ Number of dependent variables;
$k \rightarrow$ Number of independent variables treated as parameters.
$y_{art} \rightarrow$ Dependent variables related to artificial devices;
$y^+ \rightarrow$ Dependent variables;
$y^+(x,p) = y(x,p) \cup y_{art}(x,p)$

$d \rightarrow$ Number of variables associated with artificial devices;
$\gamma \rightarrow$ Penalty factor associated with artificial devices;
$\theta \rightarrow$ Penalty factor associated with the violation of restrictions of inequality;
min , max $\rightarrow$ Minimum and maximum values of the decision variables.

The values of all dependent variables (y) are determined for each set of decision variables (x) and parameters (p) through the superstructure simulation. The independent variables are treated as parameters and its values are kept constant during optimization. The decision variables are changed throughout the optimization routines during the search for the optimum.

Artificial devices were developed and included in the superstructure model to prevent simulation failures due to physical inconsistencies. When used, these devices are analogous to inviable points in some mathematical optimization techniques (Edgar and Himmelblau, 1988). If, at the end of the optimization, there is still some $y_{art}(x,p) \neq 0$, the solution is physically meaningless.

The objective function F, to be minimized, is the cogeneration plant cost per unit time. It is described in Equation 2 where the subscripts refer to the global energy system shown in Figure 1.

$$F = c_2\dot{E}_2+\dot{Z}_{Boiler}+c_3\dot{E}_3+c_4\dot{E}_4+\dot{Z}_{MCI}+\dot{Z}_{HRSG_MCI}+c_5\dot{E}_5+c_6\dot{E}_6+\dot{Z}_{TG}+\dot{Z}_{HRSG_TG}+c_1\dot{E}_1+c_7\dot{E}_7-P_{15}\dot{E}_{15}-P_{17}\dot{E}_{17}. \quad (2)$$

where,
$c \rightarrow$ specific costs of exergy fluxes ($\dot{E}$);
$\dot{E} \rightarrow$ exergy fluxes;
$\dot{Z} \rightarrow$ costs per unit of time associated with the investment of capital in the acquisition of equipment and their costs of operation and maintenance, as defined in Bejan et all (1996);
$P \rightarrow$ selling prices.

3.1 OPTIMIZATION VARIABLES

The set (X) of decision variables is divided into sets of parametric variables (X_1) and structural variables (X_2), shown below:
$X = \dot{m}_{10}, \dot{m}_{11}, \dot{E}_{12}, \dot{m}_{13}, \dot{E}_{14}, \Delta T_{Boiler}, \eta_{MCI}, \Delta T_{MCI-HRSG}, \eta_{TG}, \Delta T_{TG-HRSG}$
$X_1 = \Delta T_{Boiler}, \eta_{MCI}, \Delta T_{MCI-HRSG}, \eta_{TG}, \Delta T_{TG-HRSG}$
$X_2 = \dot{m}_{10}, \dot{m}_{11}, \dot{E}_{12}, \dot{m}_{13}, \dot{E}_{14}$

where,
$\dot{m}_{10} \rightarrow$ boiler mass flow;
$\dot{m}_{11} \rightarrow$ mass flow of the internal combustion engine recovery boiler;
$\dot{m}_{13} \rightarrow$ mass flow of the gas turbine recovery boiler;
$\dot{E}_{12} \rightarrow$ power of the internal combustion engine;
$\dot{E}_{14} \rightarrow$ power of the gas turbine;
$\eta_{MCI} \rightarrow$ efficiency of the internal combustion engine;
$\eta_{TG} \rightarrow$ efficiency of the gas turbine;
$\Delta T_{Boiler} \rightarrow$ lowest temperature difference of the boiler;
$\Delta T_{MCI-HRSG} \rightarrow$ lowest temperature difference of the internal combustion engine recovery boiler;
$\Delta T_{TG-HRSG} \rightarrow$ lowest temperature difference of the gas turbine recovery boiler.

The structural variables define the cogeneration system configuration, i.e., which equipments exist and what are their capacity. The parametric variables basically defines the equipment performance indexes.

3.2 GENETIC ALGORITHM

To perform structural and parametric optimization of the superstructure modeled in this work a stochastic optimization procedure, based on genetic algorithm, was developped and integrated with a process simulator. These technique have been previously used by Manolas et al. (1996), Valdés (2003), Cordeiro (2007) and Koch (2007) for the optimization of thermal systems.

Proposed by Holland (1975), the Genetic Algorithm is based on the Darwinian evolution of species and genetic principles. The algorithm provides a mechanism for parallel and adaptive search based on the principle of survival of the fittest. The mechanism is derived from a population of individuals (potential solutions), represented by chromosomes (binary words, vectors, matrices, etc.), each associated with a fitness (evaluation of the solution). The individuals are undergoing a process of evolution based on selection, reproduction, crossover and mutation criterias during several cycles refered as generations. This algorithm can be applied to complex problems characterized for having large search space, difficult modelling and for which there is no efficient algorithm available.

According to Whitley (2001) and Biegler (2004) the genetic algorithms differ from traditional search procedures mainly for not working with just one point, but with a set of these, using the optimization functions alone, without need for derivatives or other auxiliary calculations, simple programming and good results even when dealing with multimodal functions. The population size is a parameter that is defined considering the solution search space coverage and computational time. A population of fifty individuals was used and the chromosomes were represented by floating point.

Figure 3 presents the genetic algorithm schematics. The algorithm is a real-coded genetic and uses four genetic operators: reproduction, crossover, mutation and forced elitism. The reproduction technique is based in the binary tournament selection. As the name suggests, tournaments are played between two solutions and the better solution is chosen and placed in a population slot. Two other solutions are picked again and another population slot is filled up with the better solution. According to Goldberg and Deb (1991), it has been shown that the tournament selection has better convergence and computational time complexity properties compared to any other reproduction operator that exist in the literature, when used in isolation.

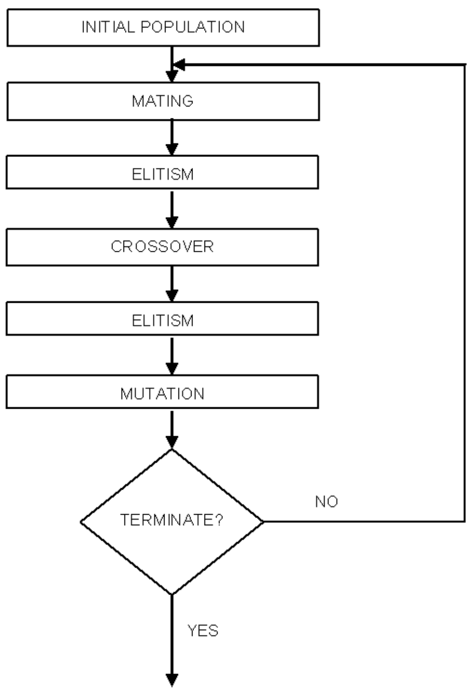

Figure 3. Schematics of the genetical alghorithm used in the optimization process.

To guarantee that no best individual is lost through generations, the algorithm comprises forced elitism. This technique allows, in parallel, high crossover and mutation probabilities. This technique has been compared with triggered hypermutation and random immigrants with better results.

The genetic algorithm has no mathematical convergence proof. Thus there are some criterias used, such as the observation of convergence of the population, which occurs when virtually all individuals are identical copies of the same sequence of genes, maximum number of generations predefinition, limiting the processing time, etc. Two criteria were adopted: to stop at a maximum of 500 generations or to stop if the best objective function value remains unmodified for fifty generations. For industrial purposes, the values adopted are conservative and can be quite decreased to reduce computational time.

3.3 FLEXIBLE POLYHEDRA

Flexible polyhedra is a direct mathematical method of optimization, originally presented by Nelder & Mead (Edgard and Himmelblau, 1988). This method was originally designed to treat problems of optimization without constraints involving continuous variables.

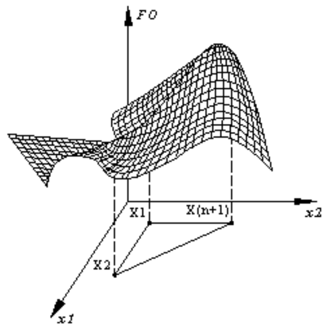

Figure 4. Construction of the initial polyhedra.

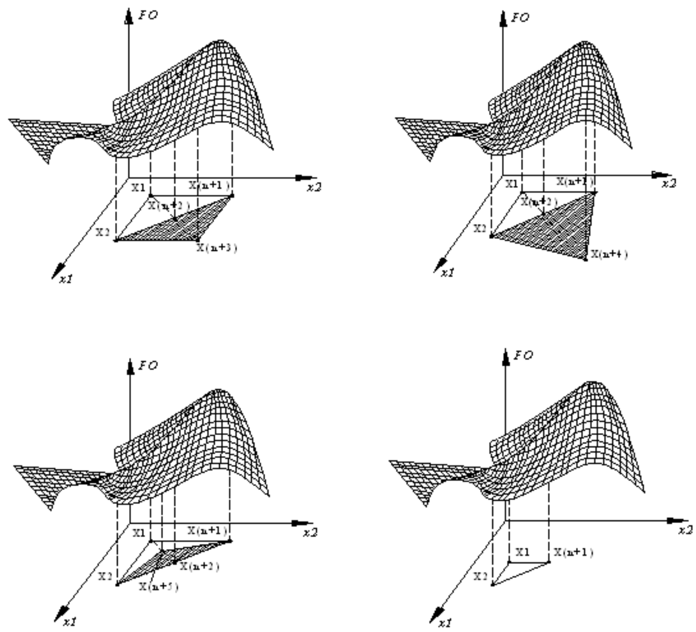

Figure 5. Basic operations: reflection, expansion, contraction/reversion and reduction, respectively.

In this method an objective function, with n decision variables, is optimized using a flexible polyhedra with $n + 1$ space vertex. The vertex i is defined by the values assigned to decisions variables in the vector Xi. The vertex with the largest value of the objective function $(f(X))$ is reflected through the center of the polyhedra, which is determined based on the other vertices. Objective function improved values are achieved by successive substitutions of the $f(X)$ highest value point. So, on the end of this process, the point with the objective function lowest value is reached.

The flexible polyhedra method stop criterion is given on the equation below, where ϵ is a relatively small number prescribed by the user.

$$\left\{ \frac{1}{n+1} \sum_{i=1}^{n+1} [f(X_i^k) - f(X_{n+2}^k)]^2 \right\}^{1/2} \leq \quad \epsilon \tag{3}$$

4. RESULTS

The methodology presented adequate results pertaining the complex problems evaluated. Two problems were analysed. The problems were used to evaluate product cost convergence characteristics and optimization time. Altogheter, the problems were defined with rather extreme concessionaire eletricity costs to evaluate the methodology robustness to achieve optimums, independently of the evaluated scenarios.

The test cases presented herein have very different boundary conditions. These conditions are presented in Table 1, and Table 2 shows the results obtained.

Table 1. Test Cases Boundary Conditions

Boundary Conditions	Test case 1	Test Case 2
Eletricity cost [US$/kWh]	0.14	0.02
Eletricity demand [MW]	10	5
Low pressure steam demand [kg/s]	5	2.5
Medium pressure steam demand [kg/s]	5	2.5

In Figures 6 and 7, the product cost minimization is presented for the genetic algorithm and flexible polyhedra best individuals along each generation/iteration considering test cases 1 and 2, respectively. Significant product cost reductions ocurred in less than 50 generations on both methods. After the initial steep decrease, the slope becomes rather flat and there is slight improvements in cogeneration plant costs.

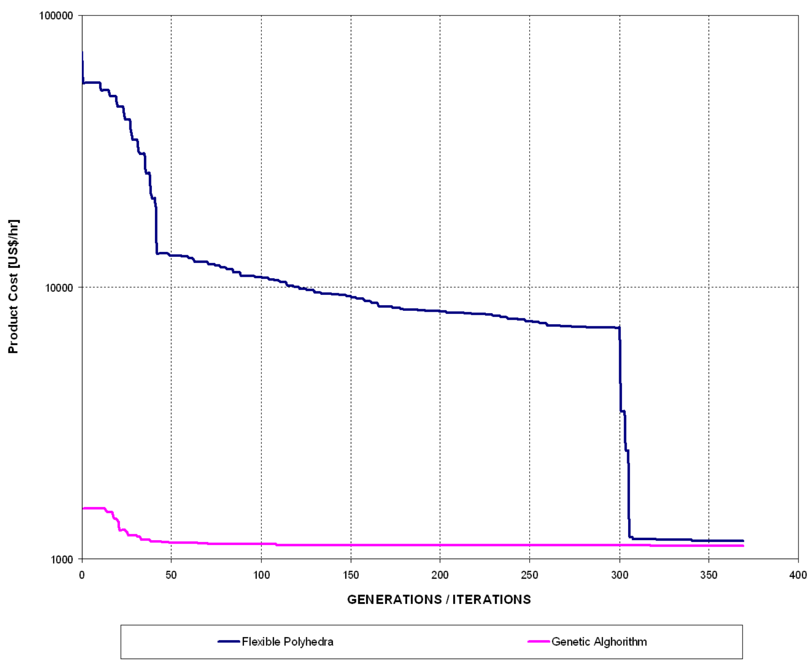

Figure 6. Test case 1 product cost minimization.

The boiler supplies most of steam demand. In test case 1, high eletricity cost enhance internal combustion engine roll in steam production. However, with low eletricity cost, the concessionaire and boiler play major roles in supplying eletricity and steam.

Since several uncertainties are involved in the estimated investment costs and in the assumptions within the economic analyses, it might be inappropriate and misleading to strive for a high precision minimal product cost. The optimization

Table 2. Test Cases Results

DESCRIPTION		Case 1		Case 2	
		GA	FP	GA	FP
PARAMETRIC VARIABLES					
Boiler	ΔT_{Boiler}	15.3	104.9	16.8	64.3
TG−HRSG	$\Delta T_{TG-HRSG}$	87.7	149.8	101.6	63.9
MCI−HRSG	$\Delta T_{MCI-HRSG}$	36.1	107.5	76.9	91.4
TG	$\eta[\%]$	19.7	27	9	21
MCI	$\eta[\%]]$	26	38	22	3
STRUCTURAL VARIABLES					
Boiler	$[kg/s]$	5.4	4.9	4.32	2.97
TG−HRSG	$[kg/s]$	1.75	4.4	0.05	1.89
MCI−HRSG	$[kg/s]$	2.95	0.7	0.63	0.05
TG	$[kW]$	1718.2	6816.7	8.9	1883.7
MCI	$[kW]$	8264.8	3183.5	1760.5	253.5
RELATIVE CAPACITY ANALYSIS					
Boiler	$[\%]$	53.6	49	86	59
TG	$[\%]$	17.5	44.1	0.1	37
MCI	$[\%]$	29.5	4.2	12.6	1
TG−HRSG	$[\%]$	17.3	68.1	0.1	37
MCI−HRSG	$[\%]$	82.6	31.8	35.2	5
CONCESSIONAIRE	$[\%]$	0.2	0	64.6	57.2
OPTIMIZATION SUMMARY					
GENERATIONS		369	806	500	1176
IPSEPRO CALLS		21609	3039	29306	4243
PRODUCT COST	$[US\$/hr]$	1119	1165.8	412.7	457.3
CONCESSIONAIRE	$[kW]$	17	0	3230.5	2862

processes are quite fast, having lasted around 5 hours using genetic algorithm and 3 hours using flexible polyhedra in a pentium, single processed, personal computer.

The following table shows the test cases summary. The advantages of applying the genetical algorithms over flexible polyhedral are remarkable. For test case 2, the cogeneration plant conceived based on genetic algorithm has an estimated product cost 21% lower than using flexible polyhedral.

5. CONCLUDING REMARKS

Many degrees of freedom, complex interactions among the plant components and the associated difficulties in achieving convergence by selecting appropriate values for process variables makes the optimization a challenging task. The larger the superstructure complexity and number of decision variables, more difficulties arise and the superstructure development becomes more time consuming.

The process optimizations considered variations in the market electricity costs and steam and eletricity requirements. Fuel cost oscillation was not evaluated. The optimization consistently defines the structure with the best settings from an economic viewpoint. The results obtained are coherent with design assumptions. Altogether an economic analysis provides additional information for identifying the real cost sources in the design, and options to reduce the total cost. A comprehensive discussion of the economic analysis, evaluation and optimization techniques is provided in Araujo (2008).

Genetic algorithms are powerful tools to optimize the process structure and process variables of cogeneration power plants, since this method achieved a smaller minimum and better power plant configuration than the flexible polyhedral

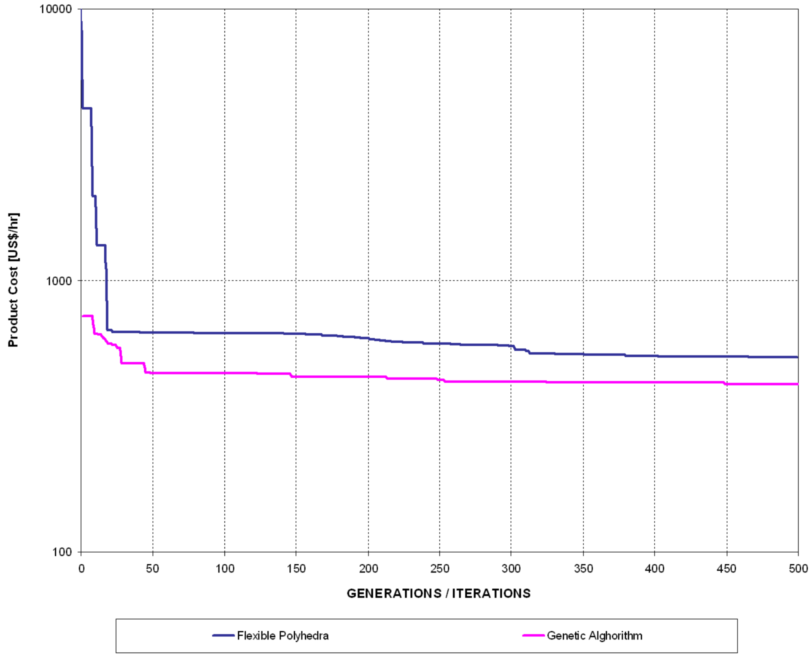

Figure 7. Test case 2 product cost minimization.

Table 3. Test Cases Summary

Boundary Conditions	Test case 1	Test Case 2
Eletricity cost [US$/kWh]	0.14	0.02
Eletricity demand [MW]	10	5
Low pressure steam demand [kg/s]	5	2.5
Medium pressure steam demand [kg/s]	5	2.5
Method		
Product Cost - FP [US$/hr]	1167	520
Product Cost - GA [US$/hr]	1119	413
Improvement due to GA	**4%**	**21%**

method. The greater computational time demanded by the genetic algorithm method is given by the fact that this method demands a larger number of IPSEpro simulation calls.

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