23rd ABCM International Congress of Mechanical Engineering
December 6-11, 2015, Rio de Janeiro, RJ, Brazil

PERFORMANCE ANALYSIS OF A THERMAL SYSTEM OPTIMIZATION USING STOCHASTIC METHODS

Leonardo Rodrigues de Araujo
Federal Institute of Espirito Santo, Av. Vitoria, 1729, Vitoria, ES, 29040-780, Brazil.
leoaraujo@ifes.edu.br

João Luiz Marcon Donatelli
Federal University of Espirito Santo, Av. Fernando Ferrari, 514, Vitoria, ES, 29075-910, Brazil.
donatelliufes@gmail.com

José Joaquim Soares Santos
Federal University of Espirito Santo, Av. Fernando Ferrari, 514, Vitoria, ES, 29075-910, Brazil.
jjcssantos@yahoo.com.br

Edmar Alino da Cruz Silva
Institute of Aeronautical Technology, São José dos Campos, SP, Brazil.
edmaralino@gmail.com

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, suchas cost estimative, design complexity, environmental protection and optimization are becoming increasingly important.Therefore the needs 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 have occurred consistent developments 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 uses of three stochastic methods (genetic algorithm, simulated annealing and particle swarm). This research work uses a superstructure, modeled in a process simulator (IPSEpro of SimTech), in which the appropriate alternatives options to design 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: *thermal system optimization, stochastic methods, genetic algorithm, simulated annealing, particle swarm.*

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 through consistent strategies and through energy conversion optimization processes. Issues such as environmental preservation, economical aspects and the very survival of humanity are increasingly demanding for energy conservation breakthroughs and processes continuing improvement and optimization. In the specifics of cogeneration plants, the complex interactions between available components, a large number of possible design alternatives and lack of cost data accurate of the equipaments, become dificult the designers ability to achieve an optimum solution (Araujo, 2008).

The design and optimization of thermal systems, including cogeneration plants, have evolved over time with the development and application of techniques and methods suitable for this purpose (Boehm, 1997). Is to mention the development and implementation of process simulators, which simplifies modelling elaboration, including superstructures, and facilitates evaluation for adequacy and performance of several mathematical optimization methods, which are then applied in thermal systems design.

Heuristic rules are often applied in the design and improvement of energy conversion systems to master the complexity of such systems and the uncertainties involved in some design decisions. A cost-effective power plant is quite sensitive to changes in the plant component configuration. Thus, a complex process flow sheet, including several optional design configurations (superstructure), is developed to enable the evaluation of many design solutions. The optimization algorithm can not create new design configurations which are not already included in the superstructure and, hence, the process designer might overlook some promising design configurations when the superstructure is developed. It is the task of the stochastic methods to select the most suitable process structure and to determine the optimal values of the process parameters that best fulfill the design objective, i.e., minimum cost.

In this context, the major objective is to pursue a performance comparative analysis of a structural and parametric cogeneration system optimization by use stochastic methods (genetic algorithm, simulated annealing and particle swarm), using a superstructure, modeled in the process simulator environment. The superstructure is modeled in the IPSEpro environment (SimTech, 1999) and the optimization algorithms are written in "MSExcel - Visual Basic". The optimization routines are written to work perfectly coupled with the simulator process.

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. SUPERSTRUCTURE USED TO COGENERATION PLANT OPTIMIZATION

A superstructure destined to cogeneration power plants structural and parametric optimization was designed as a large thermal system. As shown in Figure 1 the superstructure contains several basic alternatives capable of supplying, individually or in association, electricity 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 superstructures for optimization as in Maia, *et al*., (1995) , Donatelli (2002), Donatelli, *et al*., (2003) , Koch, *et al*., (2007) , Bejan, *et al*., (1996) and Silva, *et al*., (2010), and Araujo, *et al*., (2009).

The prime movers 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 electrical energy from the cogeneration power plant without imposed limits. Meanwhile, for this specific work, electrical 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 on 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: 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) and Donatelli, *et al*., (2003) . The low pressure steam is originated by the pressure reduction of medium pressure steam.

A superstructure was modeled in the IPSEpro (SimTech, 1999), a commercial process simulator software. The optimization algorithm was written in MSExcel - Visual Basic to work coupled with the 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 (Araujo, *et al*., 2010).

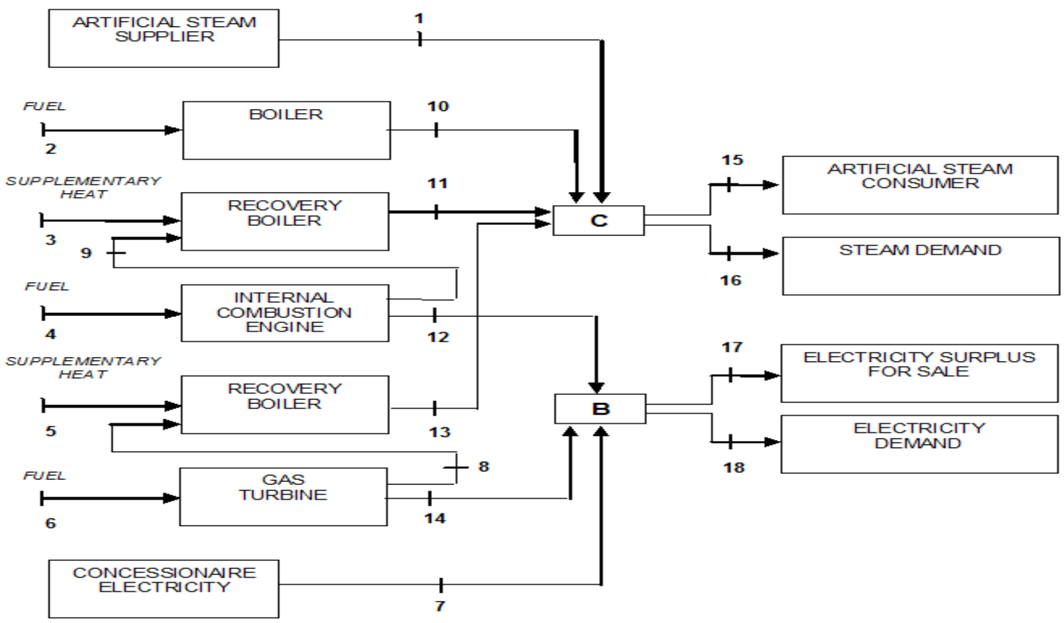

Figure 1 – Schematics of the superstructure.

3. MATHEMATICAL FORMULATION OF THE OPTIMIZATION PROBLEM

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

$$Minimize\ :\quad \hat{F}\left(x, y^{+}(x,p), p\right) = F\left(x, y(x,p), p\right) + \gamma\left(y_{art}(x,p)\right)^2 + \theta\left(g\left(x, y(x,p), p\right)\right)^2 \tag{1}$$

$$Subject\ \ to:$$

$$y^{+}(x,p) = 0$$

$$x \in \left[\min\ ,\ \max\right]$$

$$x \in \Re^{n}, y \in \Re^{m}, p \in \Re^{k}, y^{+} \in \Re^{(m+d)}, y_{art} \in \Re^{d},\ \ \hat{F}, F, \gamma, \theta \in \Re$$

Where,

$\hat{F}$: objective function including the therms of penalty.
F : objective function.
x : set of decision variables.
y : set of dependent variables.
p : set of independent variables treated as parameters.
g : restriction of inequality.
n : number of decision variables.
m : number of dependent variables.
k : number of independent variables treated as parameters.
y_{art} : dependent variables related to artificial devices.
y^{+} : dependent variables, $\{y^{+}(x,p)\} = \{y(x,p)\} \cup \{y_{art}(x,p)\}$.
d : number of variables associated with artificial devices.
γ: penalty factor associated with artificial devices, $y_{art}(x,p) > 0 \Rightarrow \gamma(y_{art}(x,p))^2 >> \hat{F}$ **.**
θ : penalty factor associated with the violation of restrictions of inequality, $g(x, y(x,p), p) \le 0 \Rightarrow \theta = 0$**,** $g(x, y(x,p), p) > 0 \Rightarrow \theta(g(x, y(x,p), p))^2 >> \hat{F}$.
min , *max* – 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 superstructure shown in Figure 1.

$$F = \begin{array}{l} c_1\dot{E}_1 + c_2\dot{E}_2 + c_3\dot{E}_3 + c_4\dot{E}_4 + c_5\dot{E}_5 + c_6\dot{E}_6 + c_7\dot{E}_7 + \dot{Z}_{Cald\_Conv} + \dot{Z}_{MCI} + \dot{Z}_{HRSG} + \dot{Z}_{TG} + \dot{Z}_{HRSG} \\ - P_{15}\dot{E}_{15} - P_{17}\dot{E}_{17} \end{array} \tag{2}$$

Where,

c: specific cost exergy fluxes.
$\dot{E}$: exergy fluxes.
$\dot{Z}$ - 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 al.*, *(*1996).
P - market price.

The set of the decision variables (x) is divided into two sets, the set of the parametric variables (x_1) and the set of the structural variables (x_2). The parametric variables are the lowest temperature difference in the boiler (ΔT_{boiler}), the lowest temperature difference in the internal combustion engine recovery boiler ($\Delta T_{MCI\text{-}HRSG}$), the lowest temperature difference in the gas turbine recovery boiler ($\Delta T_{TG\text{-}HRSG}$), the efficiency of the internal combustion engine (η_{MCI}), the efficiency of the gas turbine (η_{TG}). The structural variables are boiler mass flow (m_{10}), mass flow of the internal combustion engine recovery boiler (m_{11}), mass flow of the gas turbine recovery boiler (m_{13}) and power of the internal combustion engine (E_{12}) and of the gas turbine (E_{14}). 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.

4. GENETIC ALGORITHM

To perform structural and parametric optimization of the superstructure modeled in this work a stochastic optimization procedure, based on genetic algorithm, was developed 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 2 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.

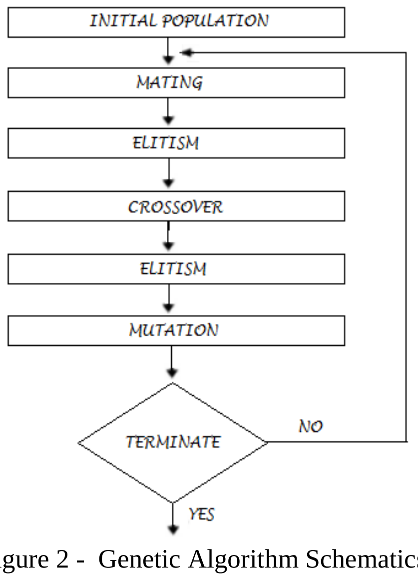

Figure 2 - Genetic Algorithm Schematics.

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 population convergence, which occurs when virtually all individuals are identical copies of the same sequence of genes, maximum number of generations or function evaluations predefinition, limiting the processing time, etc. The adopted criteria was to stop at a maximum of 5500 function evaluations. For industrial purposes, the values adopted are conservative and can be quite decreased to reduce computational time.

5. SIMULATED ANNEALING

In 1953, Metropolis, *et al.*, (2008) developed a Monte Carlo method for calculating the properties of any substance which may be considered as composed of interacting individual molecules. With this so-called "Metropolis procedure" stemming from statistical mechanics, the manner in which metal crystals reconfigure and reach equilibria in the process of annealing can be simulated. This inspired Kirkpatrick, *et al.*, (1983) to develop the Simulated Annealing (SA) algorithm for global optimization in the early 1980s and to apply it to various combinatorial optimization problems (Weise, 2009).

Simulated Annealing is an optimization method that can be applied to arbitrary search and problem spaces. Like simple hill climbing algorithms, Simulated Annealing only needs a single initial individual as starting point and a unary search operation.

Figure 3 presents simulated annealing schematics. A solution, herein designated individual, randomically generated is evaluated. Based on a predefined initial temperature and the present individual a new individual is created. The new individual is assessed and according on its fitness and energy it may be preserved over the elder individual. Along iterations the temperature is decreased in continuous steps. The stepwise temperature decrease enhances exploitative behavior in the optimization initial phases and also enhances exploration in latter phases (Weise, 2009).

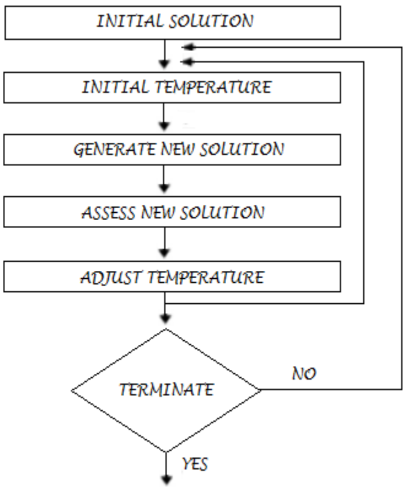

Figure 3 - Simulated Annealing Algorithm Schematics.

6. PARTICLE SWARM

Particle swarm (PS) is another evolutionary method of optimization developed by Eberhart and Kennedy (1995), which was inspired by the social behavior of bird flocking and fish schooling. PS has its roots in artificial life and social psychology, as well as in engineering and computer science. It utilizes a “population” of particles that fly through the problem hyperspace with given velocities. At each iteration, the velocities of the individual particles are stochastically adjusted according to the historical best position for the particle itself and the neighborhood best position. Both the particle best and the neighborhood best are derived according to a user defined fitness function (Eberhart and Kennedy, 1995). The movement of each particle naturally evolves to an optimal or near-optimal solution.

The word “swarm” comes from the irregular movements of the particles in the problem space, now more similar to a swarm of mosquitoes rather than a flock of birds or a school of fish (Eberhart, *et al.*, 2001).

PS is a computational intelligence-based technique that is not largely affected by the size and nonlinearity of the problem, and can converge to the optimal solution in many problems where most analytical methods fail to converge. It can, therefore, be effectively applied to different optimization problems in power systems (Del Valle, *et al.*, 2008).

Figure 4 presents the basic steps of the PS algorithm.

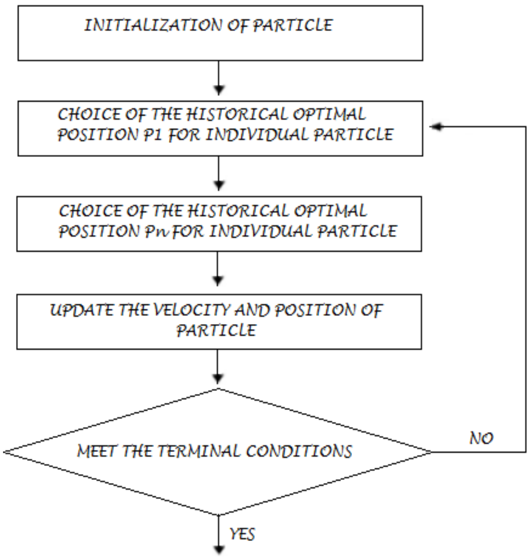

Figure 4 - Particle Swarm Algorithm Schematics.

7. RESULTS

The methodology defined to assess the performance of the methods was the optimization of the superstructure using the stochastic methods, genetic algorithm, simulated annealing and particle swarm, given the boundary conditions as shown in Table 1, evaluating the objective function (cost), convergence characteristics and optimum point. It should be noted that the problem was defined with extreme cost of utility electricity to assess the robustness of the methodology to achieve optimal points, regardless of scenarios evaluated. Table 2 shows the obtained results.

Table 1. Test Case Boundary Conditions

Boundary Conditions	Test Case
Electricity Cost [US$/kWh]	0.14
Electricity Demand [MW]	10
Low Pressure Steam Demand [kg/s]	5
Boundary Conditions [kg/s]	5

In Figure 5 the product cost minimization is present for the genetic algorithm, simulated annealing e particle swarm best individuals along each generation/function evaluation considering test cases. Significant product cost reductions occurred in less than 500 function evaluations on both methods. It is observed that the simulated annealing and particle swarm optimization provided a more severe during the first developments with respect to genetic algorithm after the initial steep decrease, the slope becomes rather flat and there is slight improvements in cogeneration plant costs.

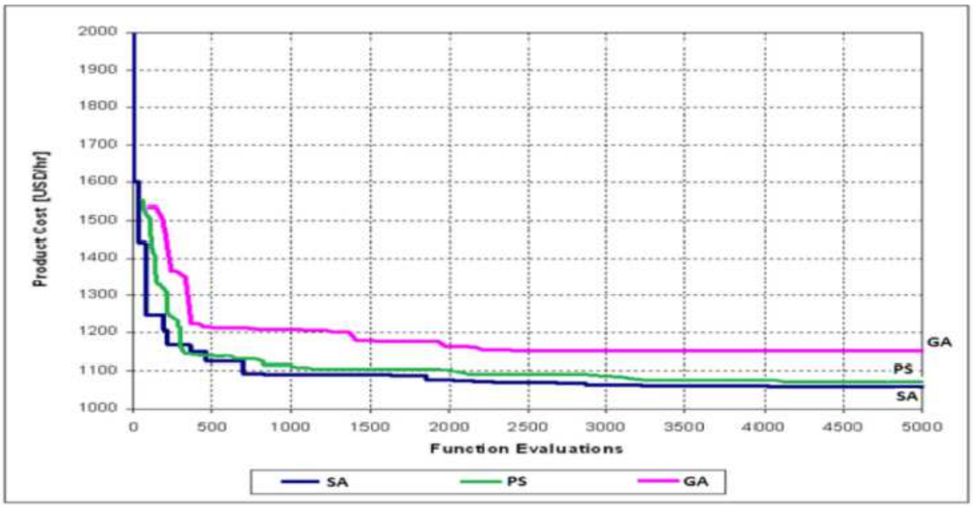

Figure 5 - Test case product cost optimization.

Table 2. Test Case Results

OPTIMIZATION METHODS	**GA**	**SA**	**PS**
PARAMETRIC VARIABLES			
BOILER [ΔT_{boiler}]	15.3	104.9	99.7
TG-HSRG [$\Delta T_{TG-HRSG}$]	87.7	149.8	138.8
MCI-HSRG [$\Delta T_{MCI-HRSG}$]	36.1	107.5	102.8
TG [η_{TG}]	19.7	27	23
MCI [η_{MCI}]	26	38	34
STRUCTURAL VARIABLES			
BOILER [kg/s]	5.4	4.9	4.6
TG-HSRG [kg/s]	1.75	4.4	3.8
MCI-HSRG [kg/s]	2.95	0.7	0.4
TG [kW]	1718.2	6816.7	5787.4
MCI [kW]	8264.8	3183.5	3964.4
RELATIVE CAPACITY ANALYSIS			
BOILER [%]	53.6	49.4	46.7
TG-HSRG [%]	17.5	44.1	38.4
MCI-HSRG [%]	29.5	7.2	4.3
TG [%]	17.2	68.2	57.9
MCI [%]	82.6	31.8	39.6
CONCESSIONAIRE	0.2	0	2.25
OPTIMIZATION SUMMARY			
IPSEpro CALLS	5500	5500	5500
PRODUCT COST [US$/hr]	1149	1058	1077
CONCESSIONAIRE [kW]	17	0	25

Observing the optimization performed by the methods described above, it has in all cases the majority of the steam generated in the process is form the conventional boiler and the remainder is produced in the recovery boiler equipment coupled to provide electrical power, internal combustion engine or gas turbine. The genetic algorithm optimization to choose the generation of most of the energy in the internal combustion engine while the simulated annealing end the particle swarm chose the generation of most of the energy in the gas turbine, since the high cost of electricity supplied.

Since many uncertainties involved in estimating costs and hypotheses in economic analysis and modeling, can be inappropriate and misleading to fight for a minimum cost of high precision product, since the models developed were not fed with accurate real behavior data. The optimization procedures were quite rapid, and each lasted about 90 minutes on a Pentium, single processed personal computer.

8. CONCLUDING REMARKS

Many degrees of freedom, complex interactions between the components of the plant and difficulties associated with the convergence of the problem causes the selection of appropriate values for the process variables is a challenging task. The greater the complexity of superstructures and number of decision variables, more difficulties arise for optimization, making the time-consuming process. During the optimization process were not considered variations in costs and demands for electricity and steam. Fuel cost fluctuations were not evaluated.

All optimization algorithms consistently define the structure with the best settings from an economic point of view, achieving the objective of this work was the structural optimization and parametric superstructure proposal through a thermoeconomic analysis. Details techniques of economic analysis, evaluation and optimization is provided in Araujo (2008) and Donatelli (2002).

The optimization using the SA and the PS obtained at lower cost than using the GA and similar plant configuration. This can be explained because the SA and PS are more easier to implement and less parameters to adjust, each individual remembers his own previous best value, as well as the region of the better; therefore, has a memory capacity more effectively than GA, SA and SP is more effective at maintaining diversity, once all individuals using the information related to the individual greater success, while in the GA, the solutions worst are discarded and only the good are saved; therefore, GA population revolves around a subset of the best individuals.

Genetic algorithms are powerful tools for the optimization of thermal systems, since this method already presented good results in comparison with the flexible polyhedron method (Araujo, 2008). Therefore it is recommended to repeat tests to assess the consistency of the GA, adjusting its parameters.

9. REFERENCES

Araújo, L. R., 2008. “Análise Comparativa da Otimização de Sistemas de Cogeração Através de um Método de Busca Direta e um Estocástico Utilizando Superestrutura e Simulador de Processo”. Dissertação de Mestrado, UFES, Brasil.

Araujo, L. R., Donatelli, J. L. M., Silva, E., 2009. “Structural and Parametric Optimization of Cogeneration Power Plants Using Genetic Algorithm”. *Proceeding of ECOS 2009.*

Araujo, L. R., Donatelli, J. L. M., Silva, E., Azevedo, J., 2010. “Comparative Analysis of Cogeneration Power Plants Optimization Based on Stochastics Methods Using Superstructure and Process Simulator”. *Proceeding of ENCIT 2010.*

Bejan, A., Tsatsaronis, G., Moran, M., 1996. Thermal Design and Optimization, John Wiley & Sons, New York, EUA.

Biegler, L., Grossmann, I., 2004. “Retrospective on Optimization, Computers and Chemical Engineering”, v. 28, pp. 1169-1192.

Boehm, R., 1997. “Introduction and Trends in the Thermal Design Field”, In: Boehm, R. F. (ed.), Developments in Design of Thermal Systems, Chapter 1, Cambridge University Press, UK.

Cordeiro, A., 2007. “Otimização e Melhoramento Exergoeconômico de Sistemas Térmicos Modelados em um Simulador de Processos Utilizando Métodos de Busca Direta e Estocástico”, Dissertação de Mestrado, UFRJ, Rio de Janeiro, Brasil.

Del Valle, Y., Venayagamoorthy, G., Mohagheghi, S., Hernandez, J., Harley. R., 2008. “Particle Swarm Optimization: Basic Concepts, Variants and Applications in Power Systems”. *Proceeding IEEE Transactions on Evolutionary Computation, Vol. 12, N. 2, April 2008.*

Donatelli, J. L. M., 2002. “Otimização Estrutural e Paramétrica de Sistemas de Cogeração Utilizando Superestruturas”, Tese de Doutorado, UFRJ, Rio de Janeiro, Brasil.

Donatelli, J. L. M., Vieira, L., Cruz, M., 2003. “Application of Superstructures to the Optimization of Cogeneration Systems”. *Proceeding of COBEM 2003.*

Eberhart, R., Kennedy, J., 1995. “Particle swarm optimization,” in Proc. IEEE Int. Conf. Neural Netw. (ICNN), Nov. 1995, vol. 4, pp. 1942–1948.

Eberhart, R., Shi, Y., Kennedy, J., 2001. “Swarm Intelligence”. San Mateo, CA: Morgan Kaufmann, 2001.

Edgar, T., Himmelblau, D., 1988. Optimization of Chemical Processes, McGraw Hill, EUA.

El-Sayed, Y., Gaggioli, R., 1989. “A Critical Review of Second Law Costing Methods - Part I: Background and Algebraic Procedures, Part II: Calculus Procedures”, Transactions of the ASME, Journal of Energy Resources Technology, v. 111,pp. 1 15.

Goldberg, D., and Deb, K., 1991. “A comparison of selection schemes used in genetic algorithms, In: Foundations of Genetic Algorithms”, Edited by G. J. E. Rawlins, 1991, pp. 6993.

Holland, J., 1975. Adaptations in Natural and Artificial Systems, Ann Arbor: University of Michigan Press.

Kirkpatrick, S., Gelatt, C, Vecchi, 2008. M. Optimization by simulated annealing. Science, 220(4598):671˝U680, May 13, 1983.doi:10.1126/science.220.4598.671. On-line available at http://fezzik.ucd.ie/msc/cscs/ga/kirkpatrick83optimization.pdf and http://citeseer.ist.psu.edu/kirkpatrick83optimization.html [accessed 2008-03-26].

Koch, C., Cziesla, F., Tsatsaronis, G., 2007. “Optimization of Combined Cycle Power Plants Using Evolutionary Algorithms”, Chemical Engineering and Processing 46 (2007) 1151-1159.

Maia, L., Carvalho, L., Qassim, R., 1995. “Synthesis of Utility Systems by Simulated Annealing”, Computers Chem. Engng., v.19. n. 4, pp. 481 488.

Manolas, D., Frangopoulos, C., Gilamas, T. et al., 1996. “Optimization of an Industrial Cogeneration System by Genetic Algorithm”. *Proceedings of the ECOS 1996, Stokolm, Sweden.*

Metropolis, N., Rosenbluth, A., Rosenbluth, M., Teller, A., Teller, E., 2008. “Equation of state calculations by fast computing machines”. The Journal of Chemical Physics, 21(6):1087 “U1092, June 1953.doi:10.1063/1.1699114. On line available at http://link.aip.org/link/?JCPSA6/21/1087/1 [accessed 2008-03-26].

Silva, E., Azevedo, J., 2010. “Comparative Analysis Of Optimization Algorithms For Industrial Applications”, Inverse Problems, Design and Optimization Symposium, João Pessoa, Brazil, August 25-27, 2010.

Sim Tech Simulation Technology, 1999. IPSEPro Process Simulator Environment, version 3.1.001.

Valdés, M., Durám, M., Rovira, A., 2003. “Thermoeconomic Optimization of Combined Cycle Gas Turbine Power Plants Using Genetic Algorithms”, Applied Thermal Engineering, v. 23, pp. 2169 2182.

Weise, T., 2009. “Global Optimization Algorithms”, Theory and Application, http://www.it-weise.de/ [accessed 2009-12-20].

Whitley, D., 2001. “An Overview of Evolutionary Algorithms: Practical Issues and Common Pitfalls”, Information and Software Technology, v. 43, pp. 817 831.

10. RESPONSIBILITY NOTICE

The authors are the only responsible for the printed material included in this paper.