COMPARATIVE ANALYSIS OF COGENERATION POWER PLANTS OPTIMIZATION BASED ON STOCHASTICS METHODS USING SUPERSTRUCTURE AND PROCESS SIMULATOR

Leonardo Rodrigues de Araujo, leoaraujo@ifes.edu.br
Instituto Federal do Espírito Santo, Av. Vitória, 1729, Vitória, ES, 29040-780, Brazil

João Luiz Marcon Donatelli, joaoluiz@npd.ufes.br
Universidade Federal do Espírito Santo, Av. Fernando Ferrari, 514, Vitória, ES, 29075-910, Brazil

Edmar Alino da Cruz Silva, edmaralino@gmail.com
Instituto Tecnológico de Aeronáutica, São José dos Campos, SP, 12228-900, Brazil

João Luiz F. Azevedo, joaoluiz.azevedo@gmail.com
Instituto de Aeronáutica e Espaço, CTA/IAE/ALA, São José dos Campos, SP, 12228-903, Brazil

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 system design, such as cost estimative, design complexity, environmental protection and optimization are becoming increasingly important. Therefore the need to understand the mechanisms that degrade energy, improve energy sources use, reduce environmental impacts and also reduce project, operation and maintenance costs. In recent years, a consistent development of procedures and techniques for computational design of thermal systems has occurred. In this context, the fundamental objective of this study is a performance comparative analysis of structural and parametric optimization of a cogeneration system using stochastic methods: genetic algorithm (GA) and simulated annealing (SA). This research work uses a superstructure, modelled 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 MsExcel Visual Basic, in order to work perfectly coupled to 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, Stochastic Methods, Superstructure, Process Simulator.*

1. INTRODUCTION

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. Interactions among the plant components, the very large number of possible design alternatives and the lack of accurate cost data for all plant components at an early stage of the design process make the optimization of complex energy conversion systems a difficult task. 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 cannot 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 fulfil the design objective, i.e., minimum cost. To minimize the power plant costs, two stochastic methods are compared herein: genetic algorithms and simulated annealing methods. These evolutionary algorithms have empirical variables that significantly affect the optimization efficiency. Empirical parameters, such as crossover and mutation probability in genetic algorithms and the Boltzmann constant and initial and final temperature in simulated annealing procedures, are tested using standard test functions prior to actual application in power plant optimizations due to their fast computation times. Benchmark test functions, such as the Michalewicz function, were used to test the algorithms and to preset the parameters (Silva and Azevedo, 2010). 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 making. This latter feature should be stressed and is recommended by El-Sayed and Gaggioli (1989). Therefore the objective of this study is a comparative analysis of cogeneration power plant optimization with stochastic methods using superstructure and process simulator (IPSEpro). The cogeneration power plants are optimized with an economic viewpoint.

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.

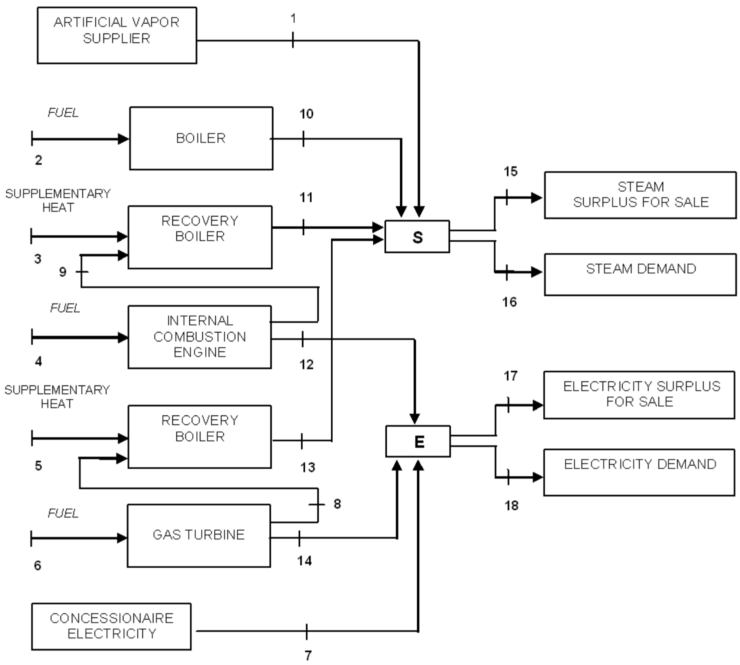

Figure 1. Schematics of the superstructure.

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, 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, Carvalho and Qassim (1995), Donatelli (2002), Koch et al (2007), Bejan, Tsatsaronis and Moran (1996), and Araujo, Donatelli and Silva (2009). The primary triggers considered are a gas turbine and an internal combustion engine, both fuelled 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 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: 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 artificial steam supplier and consumer. The artificial steam suppliers 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.

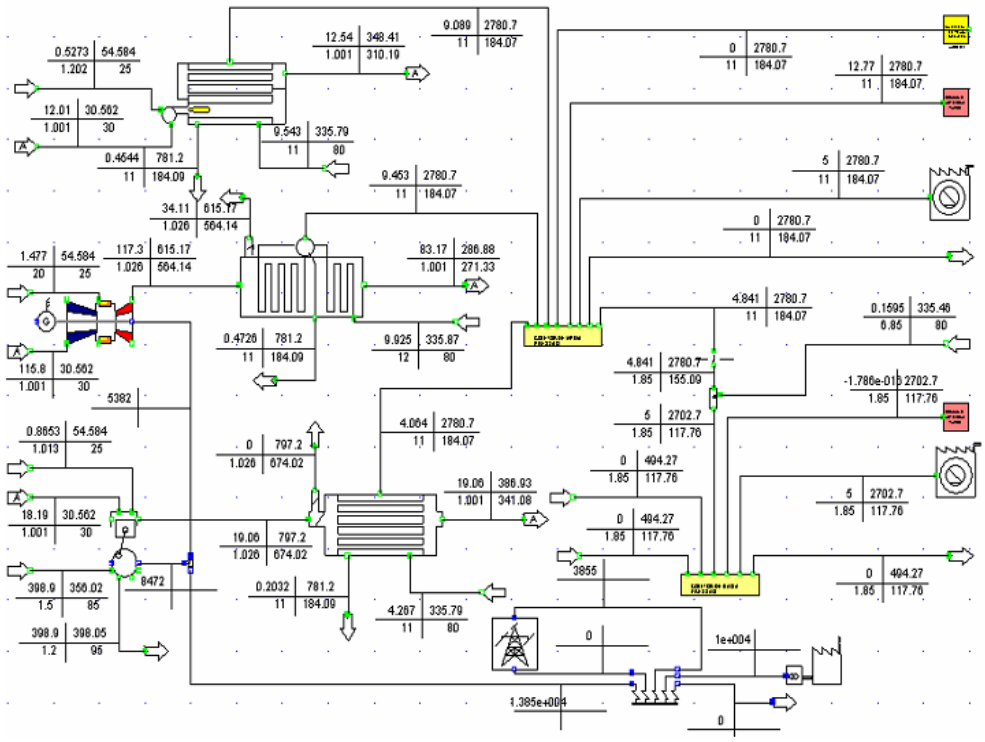

Figure 2. Superstructure as modeled in IPSEpro.

3. OPTIMIZATION

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 with market values.
Minimize:

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

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 con-

stant 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 non-viable 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 modelled 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, Durám and Rovira (2003), Cordeiro (2007) and Koch, Cziesla and Tsatsaronis (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 criteria during several cycles referred 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 and Grossmann (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 multi-modal 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.

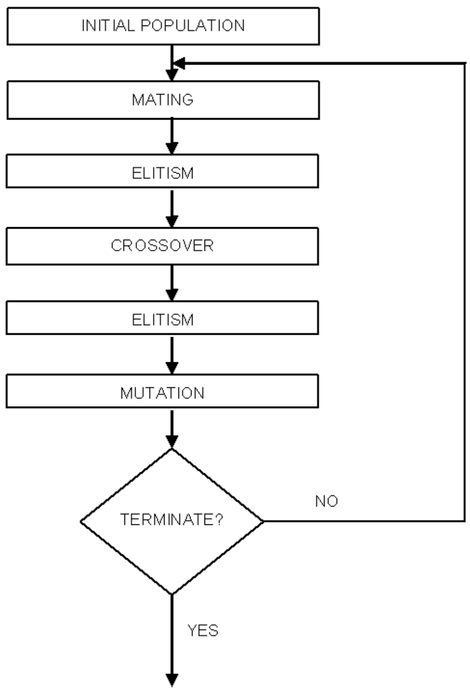

Figure 3. Genetical Alghorithm Schematics.

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 hyper-mutation and random immigrants with better results. The genetic algorithm has no mathematical convergence proof. Thus there are some criteria 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. A limiting number of function evaluations was chosen because the Simulated Annealing is not a population based algorithm and altogether not all of GA potential solutions are evaluated for each generation as some individuals are simple copies of good fitness individuals.

3.3 Simulated Annealing

In 1953, Metropolis et al. (1953) 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, Gelatt and Vecchi 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 4 presents simulated annealing schematics. A solution, herein designated individual, randomly generated is evaluated. Based on a pre-defined 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 exploitive behaviour in the optimization initial phases and also enhances exploration in latter phases (Weise, 2009).

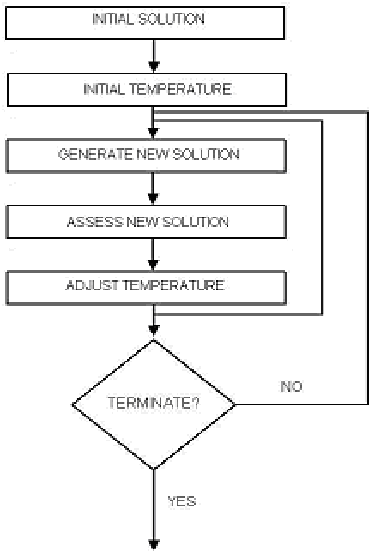

Figure 4. Simulated Annealing Algorithm Schematics

4. RESULTS

The methodologies presented adequate results pertaining the complex problems evaluated. Two problems were analysed. The problems were used to evaluate product cost convergence characteristics and optimum achieved. Altogether, the problems were defined with rather extreme concessionaire electricity costs to evaluate the methodology robustness to achieve optimums, independently of evaluated scenarios. The test cases presented herein have very different boundary conditions. These conditions are presented in Table 1. Table 2 shows the obtained results.

Table 1. Test Cases Boundary Conditions

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

In Figures 5 and 6 the product cost minimization is presented for the genetic algorithm and simulated annealing best individuals along each generation/function evaluation considering test cases 1 and 2, respectively. Significant product cost reductions occurred in less than 500 function evaluations (around 12 GA generations) on both methods. After the initial steep decrease, the slope becomes rather flat and there is slight decreases in cogeneration plant costs.

The boiler supplies most of steam demand. In test case 1, high electricity cost enhances internal combustion engine roll in steam production. However, with low electricity cost, the concessionaire and boiler play major roles in supplying electricity 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 processes are quite fast, having each lasted around 90 minutes in a pentium, single processed, personal computer. Table3 shows the test cases summary. The simulated annealing results have lower product cost than genetic algorithm results. For test case 2, the cogeneration plant conceived based on simulated annealing algorithm has an estimated product cost 26% lower than using genetic algorithm. Surprisingly, for this exact case genetic algorithm results were 21% lower than flexible polyhedral results (Araujo, Donatelli, Silva, 2009).

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 de-

Table 2. Test Cases Results

DESCRIPTION		Case 1		Case 2	
		GA	SA	GA	SA
PARAMETRIC VARIABLES					
Boiler	ΔT_{Boiler}	12.9	39.8	10.9	52.3
TG−HRSG	$\Delta T_{TG-HRSG}$	74.8	21.8	103.7	56.9
MCI−HRSG	$\Delta T_{MCI-HRSG}$	103.1	58.4	91.4	80.7
TG	$\eta[\%]$	33	19	22	21
MCI	$\eta[\%]$	30	31	32	21
STRUCTURAL VARIABLES					
Boiler	$[kg/s]$	4.2	8.0	4.7	4.8
TG−HRSG	$[kg/s]$	5.5	0.08	0.01	0.09
MCI−HRSG	$[kg/s]$	0.18	1.7	0.24	0.02
TG	$[kW]$	7357	48	206	69
MCI	$[kW]$	2633	9949	2079	66
RELATIVE CAPACITY ANALYSIS					
Boiler	$[\%]$	42	80	47	48
TG	$[\%]$	55	8	1	9
MCI	$[\%]$	1.8	17	2.4	0.2
TG−HRSG	$[\%]$	0.73	0.48	2.06	0.69
MCI−HRSG	$[\%]$	0.26	0.99	0.2	0.66
OPTIMIZATION SUMMARY					
IPSEpro CALLS		5500	5500	5500	5500
PRODUCT COST	$[US\$/hr]$	1149	1058	455	336
CONCESSIONAIRE	$[kW]$	10	3	7715	9865

Table 3. Test Cases Summary

Boundary Conditions	Test case 1	Test Case 2
Electricity cost [US$/kWh]	0.14	0.02
Electricity demand [MW]	10	5
Low pressure steam demand [kg/s]	5	2.5
Medium pressure steam demand [kg/s]	5	2.5
Method		
Product Cost - SA [US$/hr]	1059	336
Product Cost - GA [US$/hr]	1149	455
Product cost reduction	**8%**	**26%**

velopment becomes more time consuming. The process optimizations considered variations in the market electricity costs and steam and electricity 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 already presented good results compared with flexible polyhedral method Araujo, Donatelli and Silva (2009). Herein Simulated Annealing algorithm presented even lower

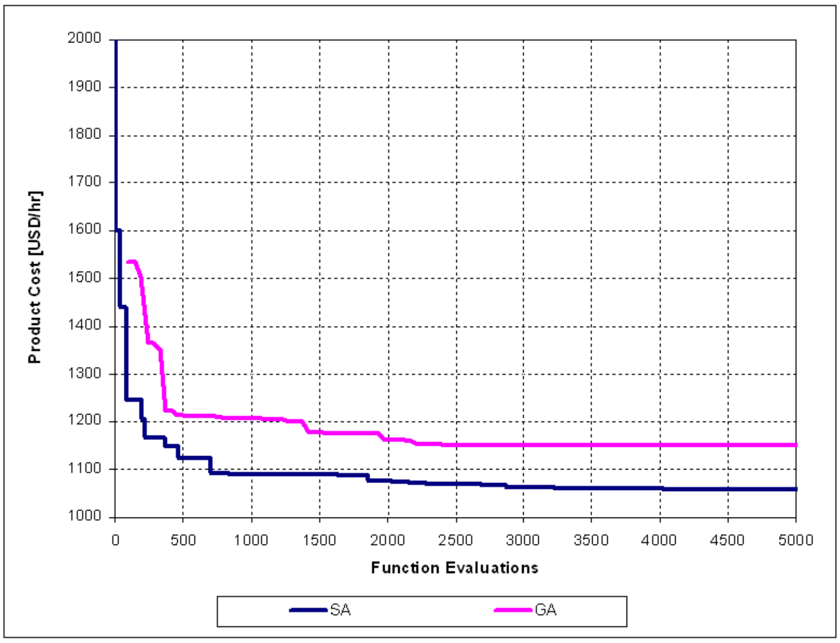

Figure 5. Test case 1 product cost minimization.

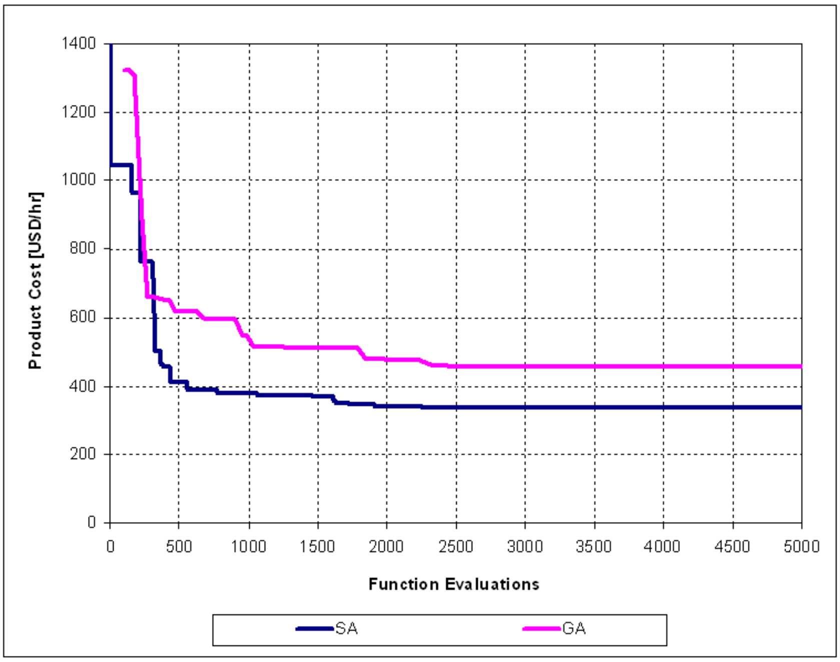

Figure 6. Test case 2 product cost minimization.

product cost. SA results are great but unexpected. SA has a unary search direction and therefore more susceptible to local optimum. Silva and Azevedo (2010) have shown that SA is less consistent than GA. Hence it is recommended repetition tests to evaluate SA consistency pertaining this specific application. Further study is being elaborated to further enhance cogeneration power plants optimizations. Enhancements are being pursued with hybridization between GA and SA to take advantage of GA consistency and SA unary search operation and optimization results. GA/SA have already been evaluated using benchmark test cases and aerodynamic optimizations with promising results (Silva and Azevedo, 2010).

6. ACKNOWLEDGEMENTS

The authors acknowledge the partial support of Conselho Nacional de Desenvolvimento Científico e Tecnológico, CNPq, under the Research Project Grant No. 312064/2006-3.

7. REFERENCES

Araújo, L. (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., Donatelli, J., Silva, E. (2009) Structural and parametric optimization of cogeneration power plants using genetic algorithm. Proceeding of ECOS 2009.

Araujo, L., Donatelli, J., Silva, E. (2009). Comparative analysis of cogeneration power plants optimization by a direct search and a stochastic method using superstructure and process simulator, Proceeding of COBEM 2009.

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. 11691192.

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.

Deb, K. (1999). An Introduction to genetic algorithms. Sadhana, 24(4), 293−315.

Donatelli, J. (2002). Otimização estrutural e paramétrica de sistemas de cogeração utilizando superestruturas, Tese de Doutorado, UFRJ, Rio de Janeiro, Brasil.

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., 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.

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

Kirkpatrick, S., Gelatt, C, Vecchi, M., Optimization by simulated annealing. Science. New Series 220 (4598): 671680. doi:10.1126/science.220.4598.671. ISSN 00368075. PMID 17813860. http://www.jstor.org/stable/1690046. Retrieved 2009−04−26.

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 , In: Proceedings of the ECOS 96, Stokolm, Sweden.

Metropolis, N., Rosenbluth, A., Rosenbluth, M., Teller, A., Teller, E., Equation of state calculations by fast computing machines. The Journal of Chemical Physics, 21(6):10871092, June 1953.

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.

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/.

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

8. Responsibility Notice