International Journal of Electrical, Electronic and Communication Sciences
ISSN: 2517-9438
Vol:4, No:3, 2010

Development of an Intelligent Tool for Planning the Operation

T. R. Alencar and P. T. Leite

***Abstract*—**Several optimization algorithms specifically applied to the problem of Operation Planning of Hydrothermal Power Systems have been developed and are used. Although providing solutions to various problems encountered, these algorithms have some weaknesses, difficulties in convergence, simplification of the original formulation of the problem, or owing to the complexity of the objective function. Thus, this paper presents the development of a computational tool for solving optimization problem identified and to provide the User an easy handling. Adopted as intelligent optimization technique, Genetic Algorithms and programming language Java. First made the modeling of the chromosomes, then implemented the function assessment of the problem and the operators involved, and finally the drafting of the graphical interfaces for access to the User. The program has managed to relate a coherent performance in problem resolution without the need for simplification of the calculations together with the ease of manipulating the parameters of simulation and visualization of output results.

***Keywords*—**Energy, Optimization, Hydrothermal Power Systems and Genetic Algorithms

I. INTRODUCTION

ON systems with a large amount of hydroelectric generation, as in the case of Brazil, you can use the potential energy of water stored in reservoirs, managing it properly, to meet demand and replace a rational generation of expensive thermal units.

However, the volume of water inflow to the reservoirs is uncertain because it depends basically on inflows that will occur in the future. Moreover, the availability of hydropower is limited by the storage capacity in reservoirs. This introduces a link between a decision to operate in a certain stage and the future consequences of this decision. For example, if the decision is to use hydroelectric power to meet the future market and a drought occurs, it may be necessary to use thermal generation of high cost or interrupt the power supply. On the other hand, if the option is the increased use of thermal generation, maintaining high levels of the reservoirs, and high flow rates occur in the future, there may be spillage in the system that represents a waste of energy and, consequently, an unnecessary increase the cost of operation [1].

Due to the characteristics, the Operation Planning of Hydrothermal Power Systems (POSHP) in Brazil can be classified as a dynamic optimization problem, large, with the objective function is not linear, non-separable and non-convex [2].

The objective of POSHP is to determine a strategy for each generation plant, which minimizes the expected value of operating costs during the planning and meet the demand within the limit of reliability. Thus, in systems with large hydro participation, the objective of economic planning of the operation is to replace, as far as possible, the generation of thermoelectric origin, high cost, for generation of hydroelectric power source, almost zero cost, in a rational way as demonstrated by [3].

The classical techniques of optimization for solving this problem may present some difficulties, mainly due to the complexity of the objective function. Thus, the search for improvements in traditional methods, or alternative approaches, aims to improve this vital step in the operation of Hydrothermal Power Systems [4].

A methodology involving Artificial Intelligence (AI) see being investigated and indicate the efficiency of the solution of several optimization problems, among them can be highlighted [2, 5-7].

The need to facilitate the editing of input data and view the results of the optimization techniques commonly used in literature, such as nonlinear programming (NLP) see triggering the production of graphical interfaces more accessible to users with different levels of training as shown in [8, 9].

Therefore, the article is to present a proposal Intelligent Tool for Object Oriented POSHP optimization, based on technical AI will guarantee a modern and easy handling for the User and that can be adopted in Planning and Operation of Hydrothermal Power Systems , as is the case of the Brazilian, who has specific characteristics that differentiate them from other systems in the world, in addition to what was proposed in [2].

The technique of AI used in this paper is inspired by the Theory of Evolution and the Nature Genetics, known as Evolutionary Computation, or Evolutionary.

Evolutionary Computation, whose research began in the 1950s, these systems to solve problems using computer

T. R. Alencar: Center for Engineering and Social Sciences (CECS) - Engineering - Grupo de Sistemas Elétricos de Potência (LABSEP), Universidade Federal do ABC (UFABC), Santo André, SP, Brasil. (ribeiro.alencar@gmail.com).

P. T. Leite: Center for Engineering and Social Sciences (CECS) - Power Engineering - Grupo de Sistemas Elétricos de Potência (LABSEP), Universidade Federal do ABC (UFABC), Santo André, SP, Brasil (patricia.leite@ufabc.edu.br).

models based on the theory of natural evolution proposes the grouping of Evolutionary Computation systems into three broad categories, these being: Genetic Algorithms (GAs), Evolution Strategies and Genetic Programming.

Optimization is the search for the best solution to a given problem. Is to try various solutions and use the information obtained in this process to find solutions that are best [10].

Heuristics are polynomial algorithms that have no guarantee on the quality of the solution, but that usually tend to find the optimal solution or be very close to it. Therefore, it should be noted that GAs are not a search algorithm of the optimal solution of a problem, but a heuristic that finds good solutions for each execution, but not necessarily the same at all times [11].

II. Methodology

The optimal operation of a power system of hydrothermal vents (HPS), with representations of individual hydroelectric (HPPs) and deterministic inputs, can be formulated as the following mathematical programming problem according to [12]. The HPS has a cost operating in a stage (t), C(t), which is defined by the cost of completion of the hydraulic system is E(t). This cost E(t) represents the difference between all the demand D(t) and all hydraulic generation H(t), including, if necessary, the lack of cargo. Equation 1 shows how the operation cost C(t) can be defined:

$$C(t) = C[E(t)^2] \quad (1)$$

where:

$$E(t) = \begin{cases} D(t) - H(t), & D(t) \geq 0 \\ 0, & D(t) \leq 0 \end{cases} \quad (2)$$

The general planning of the operation efficiency of HPS can be established as to minimize operating costs over the planning horizon t set [1, T] according to equation 3, where $f_t(.)$ Represents the function Operation Costs and C(.) non-hydraulic generation.

$$Min \quad J = \sum_{t=1}^{T} f_t[C(t)] \quad (3)$$

The total hydro generation in period t, H (t) is the sum of the generations of all hydroelectric power plants, according to equation 4, where N represents the number of hydroelectric plants, $\emptyset_i(.)$ the generation function of hydro plant i, $x_i(.)$ the volume of the reservoir i and $u_i(.)$ flow has escaped the plant i.

$$H(t) = \sum_{i=1}^{N} \emptyset[x_i(t), u_i(t)] \quad (4)$$

The function of the hydraulic power to any one plant is expressed by equation 5, where K_i is the productivity of the plant i is a constant that includes acceleration of gravity, density of water, income-generating turbine and conversion factors, in addition, $h_1(.)$ represents the polynomial volume quota, or amount of time depending on the volume of the reservoir. The term $h_2(.)$ is the polynomial flow has escaped x quota, i.e., when the function of the downstream flow fueled and poured.

$$\emptyset(x, u) = K_i[h_1(x) - h_2(u)] \min\ [u, q^{max}] \quad (5)$$

The balance equation of water defined by equation 6 relates the states of shells over time, where Ω is the set of all plants immediately upstream of the plant i.

$$x_i(t+1) = x_i(t) + y_i(t) + \sum_{k \in \Omega_i} u_k(t) - u_i(t) \quad (6)$$

The storage volume and water released by HPPs are limited by operating restrictions imposed by equations 7 and 8, where x_{min} and x_{max} represent the minimum and maximum respectively of the plant's reservoir.

Moreover, u_{min} and u_{max} represent the minimum and maximum centrifugation of the plant.

$$x_{min}(t) \leq x_i(t) \leq x_{max}(t) \quad (7)$$

$$u_{min}(t) \leq u_i(t) \leq u_{max}(t) \quad (8)$$

This paper proposes the use of genetic algorithms that are heuristic techniques of global optimization that are based on the mechanisms of natural selection and genetics. The GAs have strong dependence of the initial values in obtaining the optimal solution [11 - 17].

In addition, the GAs are not restricted by assumptions about the search space, on the continuity and existence of derivatives. Typically, searches on real problems are full of discontinuities, noise and other problems. Methods that rely heavily on restrictions of continuity and existence of derivatives are only suitable for problems in a limited domain [13].

The GAs are based initially on the generation of a population formed by a random set of individuals that can be seen as possible solutions to the problem.

During the evolutionary process, the population is evaluated for each individual is given a note, or index, reflecting its ability to adapt to a certain environment. A percentage of the fittest is retained, while other others are discarded (Darwinism). Members maintained by selection may change in its fundamental characteristics through mutation and crossover (crossover) or genetic recombination generating offspring for the next generation. This process, called reproduction, is repeated until a satisfactory solution is found [2].

An overview of the proposed algorithm is shown in Figure 1, through a flowchart with the sequence of operations used to determine the operation of the hydrothermal system, using the technique of Genetic Algorithms.

The flow chart in Figure 1 shows since the entry of the algorithm to the applications of genetic operators, calculations of skills and training of new populations. A detailed description of the main procedures is presented below.

International Journal of Electrical, Electronic and Communication Sciences
ISSN: 2517-9438
Vol:4, No:3, 2010

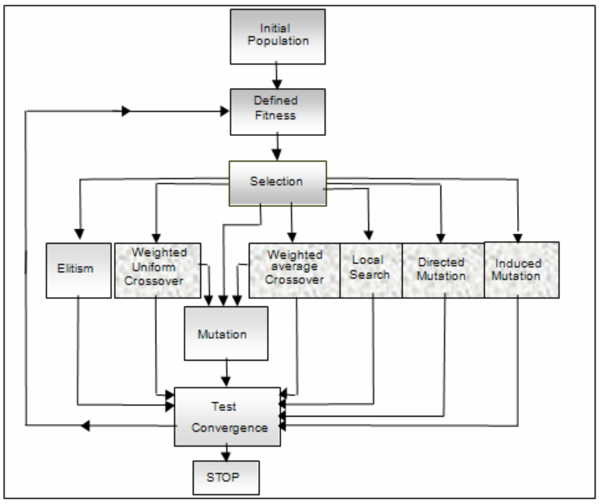

Fig. 1 Algorithm

Codification of the problem: because of the complexity of the problem, your coding must be careful to match the characteristics of plants and the planning of the operation of the plants selected for testing. The population is characterized as an array of objects, where each individual has another array of objects composed of selected plants in the graphical program entry to make up the planning of the operation. In turn each selected plant has individual characteristics such as name, code, vector surging natural centrifugation minimum and maximum, minimum and maximum operation, type of reservoir, true power plant, the polynomial coefficients of volume and centrifugation, and a vector of type double that represents the volume of the plant each month. The vector volume represents the theory of GA chromosome characteristic of the plant and the volumes of each month represent the genes of the chromosome. We adopted a real representation, not binary, as proposed in [2]. The basic structure of the encoding of the problem is shown in Figure 2.

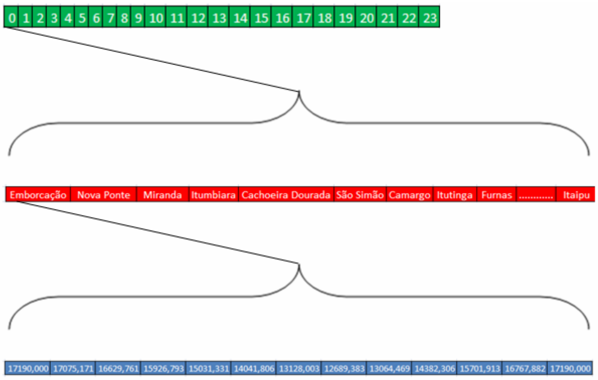

Fig. 2 Structure of the coding problem

Population size: the size of the population is directly related to the overall performance and efficiency of GAs. No problem identified after several tests with populations of different sizes, it was found that the greater the population, the greater the time required for convergence of the algorithm. Therefore, in order to run the program in a shorter time, we decided to use a population comprising 24 individuals as adopted in [2].

Initial population: the initial population can be obtained in three different ways the first being completely random, the second with an individual equal to the maximum volume of the reservoir and the remainder at random and the third with all individuals with a maximum volume of the reservoir.

Defined fitness: either the cost function is related to minimizing the value of the objective function of the problem presented above.

Ordination of the population: the population is classified by calculating the cost of all individuals and constructive examination of the restrictions and then the ordering as the objective of minimizing the problem.

Selection: The method used is the roulette. This method creates a roulette in which each individual receives a piece proportional to its score (the sum of the pieces can not exceed 100%). After the wheel is the wheel and the individual will be selected on which it stops [11].

Elitism: that the best individuals are not lost from one generation to another, applies the operator of elitism. This ensures that the best pass automatically to the next generation, preserving their genetic characteristics.

Mutation: with the objective of maintaining the diversity of the population genetic mutation operator is applied in the offspring. The mutation operator is applied with a given probability in a number of individual genes, altering its original value.

Stopping criterion: the proposed algorithm uses the number of generations User Defined as the sole criterion to stop the program.

Mask	8.0	6.0	5.0	3.0	2.0	9.0	1.0	4.0	9.0	8.0	2.0	10
Parent 1	1.0	1.0	0.92	0.85	0.73	0.61	0.49	0.65	0.74	0.83	0.93	1.0
Offspring	1.0	1.0	0.92	0.85	0.73	0.55	0.49	0.65	0.72	0.82	0.93	1.0
Parent 2	1.0	0.98	0.67	0.46	0.85	0.55	0.37	0.91	0.72	0.82	0.54	1.0

Fig. 3 Weighted uniform crossover

Weighted uniform crossover: based on uniform crossover [10], this operator uses a weighted mask considering the parent's relative fitness in the population. Thus, the genes of the fittest indivuduals have a highter chance to be selected when the genes are copied from the parents to the offspring. Figure 3 shows an example of the modified uniforme crossover with a crossover rate [11], μ, equal to 7.7. Thus, if genemask < μ, copy the corresponding gene from parent 1; otherwise, copy the correponding gene from parent 2.

Weighted average crossover: for the weighted average crossover, the value of each gene in the offspring is the weighted average of the corresponding genes in the parents.

The weighted are defined by two fitness of the parents. Figure 4 illustrates the weighted average crossover with weight= 0.8. The value of the new genes is defined by $gene_{new}$ = weight * $gene_{p1}$ + (1-weight) * $gene_{p2}$.

Parent 1	1.0	1.0	0.92	0.82	0.75	0.68	0.47	0.61	0.72	0.83	0.99	1.0
Offspring	1.0	1.0	0.91	0.82	0.76	0.69	0.50	0.66	0.72	0.85	0.98	1.0
Parent 2	1.0	1.0	0.85	0.82	0.81	0.73	0.62	0.85	0.72	0.93	0.94	1.0

Fig. 4 Weighted average crossover

Directed mutation: in the HPSOP problem, the operational costs are given by a polynomial function where there is a tendency to consider that a more uniform thermal generation along the time implies a lower operation cost. Therefore, an investigation is carried out in all the peaks that occured during the planning period to apply mutation in the volume point corresponding to all the peaks of thermal generation to maintain keep as uniform as possible, as shown in Figure 5. When using real values and not binary, second from [14], the uniform beam has a better performance.

Thermal generation before directed mutation	90	90	90	65	90	90	70	85	90	90	90	90
Individual before directed mutation.	1.0	1.0	1.0	0.82	1.0	1.0	0.85	0,95	1.0	1.0	1.0	1.0
Individual after directed mutation (Offspring)	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
Thermal generation after directed mutation	90	90	90	90	90	90	90	90	90	90	90	90

Fig. 5 Directed mutation

Induced mutation: the plants operate in cascade and have different operational characteristics, as they have different positions in the system. The upstream plants regulate the water flow, with an oscillation in their volumes, and reach the maximum volumes at the end of the planning period. On the other hand, the downstream reservoir presents maximum efficiency during the whole period, staying at the maximum level probably due to the head effect.

Based on the previous knowledge of the optimal operation of an HPS, the individuals that correspond to the upstream plants are more likely to have oscillation in their volume, while the downstream plants are kept full. This information can reduce the run time. For example, in a test system with 3 plants, the individual representing the last plant (a downstream plant - whose tendency is to keep the reservoir full) was subjected to induced mutation. The new characteristics of the third plant are shown in Figure 6.

Individual before induced mutation.	1.0	1.0	0.95	0.85	0.89	0.97	0.85	1.0	1.0	1.0	0.99	1.0
Individual after induced mutation.	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0

Fig. 6 Induced mutation

Local search: a group of individuals similar to other individuals in the same population may have a small change in their gene values. Those alterations follow the same mechanisms used in the mutation, but all genes will change except the first and the last ones. This operation aims to increase the diversity of the population as well as to explore the neighborhood of highrank individuals. New individuals with improved cost will replace the original ones in the population, as presented in Figure 7.

Individual before local search.	1.0	1.0	0.95	0.82	0.75	0.50	0.75	0.81	0.90	0.95	1.0	1.0
Individual after local search.	1.0	0.91	0.85	0.81	0.76	0.55	0.69	0.78	0.89	0.91	0.95	1.0

Fig. 7 Local Search

The intelligent software tool was developed for application to problems POSHP, where the configuration of the test system can use individual hydroelectric plants, which make up Sub-System Southeastern Brazil, with 18 plants operated the reservoir 17 and the river, as shown in Figure 8.

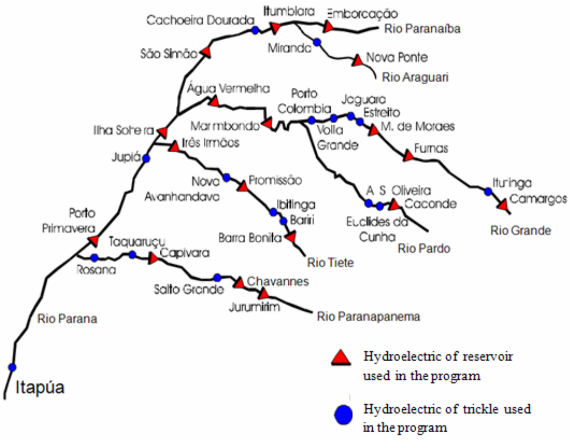

Fig. 8 Part of the Brazilian Southeast System

Adopted as the start of planning for all periods the month of May, because it is the beginning of the dry season, and as the final month of April, when the period of higher inflows, coinciding thus with the hydrological year. Inflows adopted, equal to LTA (Long Term Average), were removed from the file flow of the Brazilian. The planning period used can vary from 1 year to 5 years (with discretization monthly), and the market varies during the planning period.

The program was developed in Java, because this programming language has several visual features that facilitate handling of users to see. The traditional algorithm adopted as the standard of comparison was the non-linear programming (NLP). The output of the NLP optimization of a traditional program was included in the tool developed by reading text file.

This tool was developed using a computer with a Pentium 4, 3.2 GHz and 1 GB of memory and the programming language used is Java and C.

III. RESULTS AND DISCUSSION

When start the program displays a splash screen with a picture of the Itaipu and logos UFABC (Universidade Federal do ABC) and the research group LABSEP (Laboratory of Electrical Power Systems), as shown in Figure 9.

Fig. 9 Initial screenshots of the tool developed

The second screen is used to program the configuration of the electrical system test. Note that in Figure 10 is shown the schematic diagram of the hydro and User may select any of the power available to perform the test case study, and also for training using the tool. Another possibility is to carry out a test case using all plants in cascade, reflecting the work carried out in the electricity sector. At present, the User will see through the schematic position of the plant in the cascade in the pond and a river is installed.

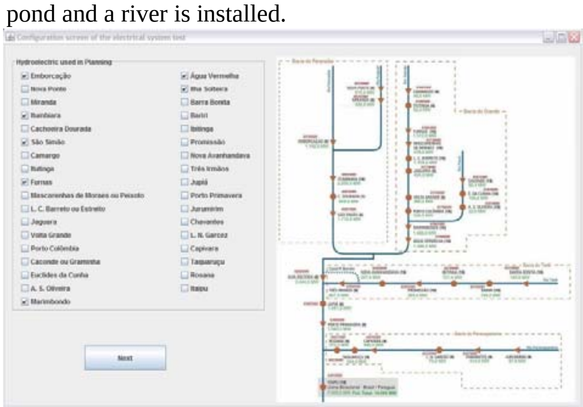

Fig. 10 Display System Configuration Test

After setting up the electrical system test the user sees the screen of the configuration parameters of genetic algorithm and the planning of the operation, as shown in Figure 11. On this screen the user can set the project name, number of generations, population size, the types of beam desired by its associated probability, type of initial population, number of point mutations and the associated probability, moreover, the number of individuals now for the next population by elitism. In addition to the parameters of the genetic algorithm described above the third screen of the program allows consumers to set the parameters of the operation planning how to select between a flat market and seasonal, the value of the cost of thermal plant operation and the choice of planning time between 1 to 5 years.

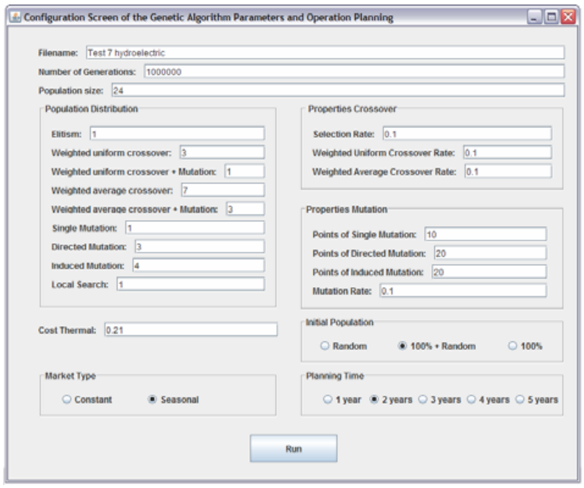

Fig. 11 Screen configuration data used by GAs

For demonstration of this tool, we adopted a test system composed of 7 hydroelectric power plants (Emborcação, Itumbiara, São Simão, Furnas, Marimbondo, Água Vermelha and Ilha Solteira), all plants are shown in Figure 8.

In Figure 11 is shown the configuration adopted for the genetic operators and the information necessary to calculate the hydro (cost of heat, type of market and planning time).

With the completion of all required settings the program is executed and at the conclusion of processing is generated three graphs, the first being the planning of hydrothermal that plots the volume of each month the plants to the best individual found by the genetic algorithm. The second graph plots the cost of operating the plan consists of the demand for each month and the results of the optimization algorithms NLP and GA, which are hydro and thermal complementation total from the difference between demand and hydroelectric. The third graph plots a comparison between the thermal output of each month estimated by NLP algorithm and GA.

The results are presented in order to verify the implementation and present the tool, highlighting its usefulness for the User you want to use it to understand the concepts involved in problem POSHP, as well as the sensitivity and use of the technique based on Artificial

Intelligence on Genetic Algorithms in comparison with the technique of nonlinear programming.

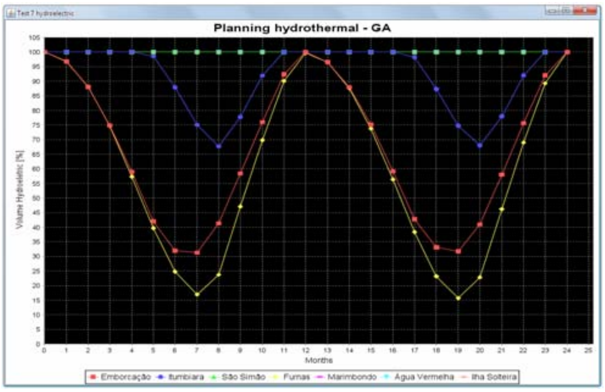

Fig. 12 Planning Hydrothermal

In Figures 12 presents the results for volume estimates for the planning of the operation by GAs. The plants involved in this test is the tank, or have the ability to accumulate water during the flood season for use in the dry season and therefore has higher flow than the minimum natural, thus to meet changing demand.

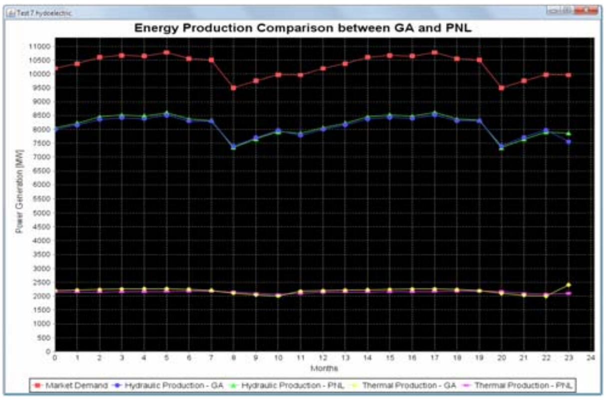

Fig. 13 Energy Production Comparison between GA and NLP

In Figure 13 is presented the comparison chart between energy production as a solution found by the NLP and AG. Looking at the graph you can see that the GAs were able to approach the result obtained by the NLP, shown the great potential of the technique based on Genetic Algorithms.

In Figure 14 shows the graph where you can make a comparison between the cost of planning the operation defined by thermal generation. The areas in red show the points where the technique of GA showed a result worse than the PNL and regions in green highlight in the months that the GAs had a lesser thermal production the NLP technique.

The difference between the areas in red and green show how the algorithm was superior in NLP optimization for the GAs. At the end of optimizing the AGs had a total cost of operation 2.2047E+7, while the technique based on NLP presented cost 2.1024E+7.

Fig. 14 Comparison of Cost of Operation Planning between GA and NLP

With the development of this tool can be structured many configurations to be tested, ranging from the number of factories, even the types of operators, for a variety of analysis involving both researchers and industry players involved in the electrical POSHP, as the area development software.

It is believed that this tool may assist in studies and action planning of the operation or even helping solving the analysis of managers Electricity Sector. Another aspect worth highlighting is that is can be used as an alternative to the tools that has been developed which use traditional techniques of optimization.

IV. Conclusion

As presented in this article, this work shows the applicability and potential of GA in the Operation Planning of Hydrothermal Power Systems. Regarding the technique adopted, several tests regarding the definition of a population size of efficient search of a more original solution to the problem and consideration of the genetic operators used can be easily seen. These reviews seek greater certainty in assessing the types of operators that are best suited to the problem. Also allow the use of special techniques, such as hybrid algorithms in conjunction with this tool, which may contribute to a better performance from it.

The results in the application of GAs showed the great potential of this tool, which managed to capture the different characteristics of power plant operation, without the need to simplify the original formulation of the problem.

This tool will help in studies and actions in planning the operation of the Brazilian Electricity Sector.

When applied in course will provide greater sensitivity to users in the implementation of energy planning and the use of optimization technique based on Genetic Algorithms.

Acknowledgment

The authors acknowledge the technical support of the *Conselho Nacional de Desenvolvimento Científico e Tecnológico* (CNPq) and *Universidade Federal do ABC* (UFABC) for enabling the development of this research.

REFERENCES

[1] E. L. Silva. Formação de Preço em Mercados de Energia Elétrica. Editora Sagra Luzzatto, (2001).
[2] P. T. Leite, A. A. F. M. Carneiro and A. C. P. L. F. Carvalho, “Energetic Operation Planning Using Genetic Algorithms”, IEEE Transaction on Power Systems, vol. 17, no. 1, February 2002, pp. 173-179.
[3] M. V. Perreira. Overview-Optimal Scheduling of Hydrothermal Systems. IFAC Symposium on Planning and Operation of Electric Energy Systems, pg. 1-9, (1985).
[4] M. E. P. Macieira and R. M. Marcato and A. L. M. Marcato. Comparação entre Abordagem Estocástica e Determinística no Planejamento da Operação de Médio Prazo de Sistemas Hidrotérmicos Interligados. XVII SNPTEE - Seminário Nacional de Produção e Transmissão de Energia Elétrica. Uberlândia - MG, Brasil. (2003).
[5] M. Basu. An interactive fuzzy satisfying method based on evolutionary programming technique for multiobjective short-term hydrothermal scheduling. Electric Power Systems, pg. 277-285. (2004).
[6] T. R. Alencar, P. T. Leite. Utilização de uma ferramenta inteligente na determinação do planejamento energético. 30° CILAMCE – Congresso Ibero-Latino-Americano de Métodos Computacionais em Engenharia. Búzios – RJ, Brasil. (2009).
[7] K. K. Mandal, M. Basu, N. Chakraborty. Particle swarm optimization technique based short-term hydrothermal scheduling. Applied Soft Computing, pg. 1392-1399. (2007).
[8] R. C. Zambon. Planejamento da Operação de Sistemas Hidrotérmicos de Grande Porte. Tese de Doutorado – Escola Politécnica da Universidade de São Paulo, (2008).
[9] T. R. Alencar, P. T. Leite. Desenvolvimento de uma Ferramenta Inteligente para o Planejamento da Operação de Sistemas Hidrotérmicos de Potência. 8th CLAGTEE - Latin-American Congress on Electricity Generation and Transmission. Ubatuba – SP, Brasil. (2009).
[10] C. O. GALVÃO e M. J. S. VALENÇA. Sistemas Inteligentes – Aplicação a Recursos Hídricos e Ciência Ambiental. Editora da Universidade, Porto Alegre, Universidade Federal do Rio Grande do Sul, ABRH, Associação Brasileira de Recursos Hídricos.1999.
[11] R. Linden. Algoritmos Genéticos - Uma importante ferramenta da Inteligência Computacional. Editora Brasport, Rio de Janeiro - RJ. 2006.
[12] A. A. F. M. Carneiro and S. Soares and P. S. Bond. A Large Scale Application of an Optimal Deterministic Hydrothermal Scheduling Algorithm. IEEE Trasaction on Power Systems. Vol. 5. n. 1. pp. 204-210. February. (1990).
[13] D. E. Goldberg. Genetic Algorithms in Search Optimization and Machine Learning. Addison-Wesley Pub. Co. (1989).
[14] D. Beasley and D. Bull and R. Martin. An Overview of Genetic Algorithms: Part 1, Fundamentals. Inter-University Commitee on Computing. (1993).
[15] M. Gen and R. Cheng. Genetic Algorithms and Enginneering Design. Reading. MA., Addison Wesley. United States of America. (1989).
[16] D. Corne, M. Dorigo and F. Glover. New ideas in optimization. David Hatter, McGraw-Hill. Vol. 1. pp. 493. Great Britain at the University Press, Cambridge. (1999).
[17] Salomon. Evolutionary Algorithms and Gradient Search: Similarities and Differences. IEEE Transactions on Evolutionary Computation. Vol. 2. n. 2. pp. 45-55. July. (1998).