

# Brazilian Energy Auctions Analysis Based on Evolutionary Algorithms

C. M. B. Castro; A. L. M. Marcato, *Senior Member, IEEE*, I. C. S. Silva Jr; B. H. Dias, *Member, IEEE*, G. E. Silva Jr; E. J. Oliveira

**Abstract - After the Electricity Market Restructuring, occurred from 2004, the distribution companies (DISTCOS) in the Brazilian Energy Market must meet their expected load through regulated contracts, made in regulated auctions. These contracts are classified accordingly to its origins, New Energy or Existing Energy, and to the beginning of supply. New Energy comes from generators that are not yet constructed, aiming at estimating long-term contracts, while Existing Energy represents generators under operation. DISTCOS must choose between those contracts so it is of great importance a computational tool that helps agents to have an optimal portfolio. Additionally, they must learn from their experience, represented by their participation in previous auctions. This work presents a new methodology using Evolutionary Algorithms, that uses genetic operators such as selection, mutation, and inheritance, in order to determine the amount of energy to be contracted in each kind of auction, taking into account the results of previous auctions.**

**Index Terms- Energy Market, Auction Theory, Evolutionary Games**

## I. INTRODUCTION

With the general crisis affecting several economic sectors in the 1980's, Brazil's growing was threatened due to the lack of investments in the power sector. Thus, during the 1990's we could observe a continuous search for an adequate structure to the power supply. At that time, many reformulations were implemented, privatizations were performed and, mainly, accentuated changes in the market

structure occurred, making this industry deverticalized through separating generation (GENCOS), distribution (DISTCOS) and transmission segments [1].

The restructuring performed at the Brazilian electricity market brought a series of new challenges to the energy agents [2]. Therefore, we can highlight the introduction of energy auction practices [3-5] as one of the most significant changes when energy trading is concerned.

On the hand of DISTCOS, the optimum portfolio is obtained considering basically two contracting modes [6 - 8]: (i) existing energy auctions – originated from the power plants already installed in the system, with contracts lasting from five to fifteen years of energy delivering; (ii) new energy auctions – originated from power plants under construction or that will be constructed in a few years, with contracts lasting from fifteen to thirty years.

Considering those possibilities of contracting energy in the Brazilian energy sector, it is fundamental the development of a computational tool in order to assist DISTCOS to obtain an optimum portfolio. This paper presents an evolutionary algorithm aiming at defining the amount of energy DISTCOS shall negotiate in each kind of auction, in order to minimize total contracting costs.

## II. ENERGY TRADING IN BRAZIL

Brazilian electricity market has been through a deep reform, such as a sector deverticalization, which triggered a change cycle. In this new market, the regulated auctions, that begun with the first existing energy auction in 2004, can be considered the main type of energy trading in the Brazilian market.

Energy auctions in the energy trade aims at meet the demand by the lower price criteria. During energy auctions, energy is commercialized, when the purchase (performed by the distributors) and sale (performed by the generators) are ruled by Energy Commercialization Agreements at the Regulated Environment. Those purchase and sale agreements can be executed in a Regulated Contracting Environment, which are bounded to the existing energy enterprises, which use the capacity installed in the system, or to the new energy enterprises, which aim at

---

C. M. B. Castro, B.Sc, is working toward his M.Sc. in Economics at Federal University of Viçosa, Brazil (e-mail: crismbc@yahoo.com.br)

I. C. Silva Jr, D.Sc, is Assistant Professor of Electrical Engineering at Federal University of ABC, Brazil. (e-mail: ivo.junior@ufabc.edu.br)

A. L. M. Marcato, D.Sc, is Assistant Professor of Electrical Engineering at Federal University of Juiz de Fora - Brazil. (e-mail: andre.marcato@ufjf.edu.br)

B. H. Dias, is a Ph.D. Student in Electrical Engineering at Pontifical Catholic University of Rio de Janeiro. (e-mail: bdias@ele.puc-rio.br)

G. E. Silva Jr, is Assistant Professor of Economics at Federal University of Viçosa - Brazil. (e-mail: gedmundos@yahoo.com.br)

E. J. Oliveira, D.Sc, is Assistant Professor of Electrical Engineering at Federal University of Juiz de Fora - Brazil. (e-mail: edimar.oliveira@ufjf.edu.br)

expanding this capacity. At the existing energy auctions, the energy contracting occurs one year before the delivering, known as A-1. At the new energy auctions, this contracting is performed from three to five years before supply starts, defined as A-3 and A-5, respectively. This fact can be observed in Figure 1, which illustrates those types of contracts at the regulated environment [7].

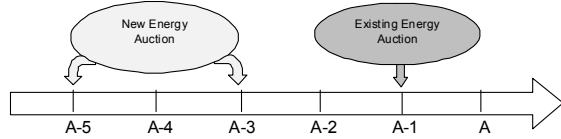


Figure 1: Brazilian Electricity Auctions

The A-1 contracts can last from five to fifteen years, while A-3 and A-5 contracts can last from fifteen to thirty years. Therefore, we enhance the importance of making a well-planned decision considering the best time and the optimal contracting amount, due to the decisions made by the power distributors are actions that will be effective for a long period, due to the other contracting possibilities and market uncertainties.

Thus, the contracting structure can be classified as a dynamic game, since several contracting possibilities occur with the time.

When analyzing the auctions realized in Brazil since 2004, one can say that the contracting prices in A-3 and A-5 were very near, but the auction prices A-3 followed a trend of a slight drop; while A-5 prices were higher.

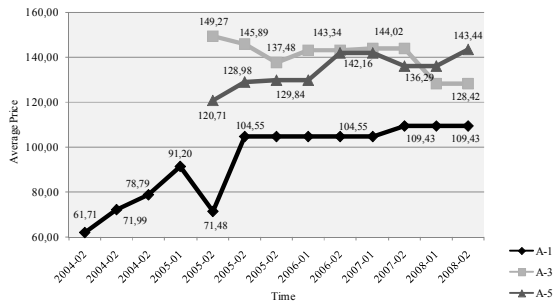


Figure 2 – Average prices comparison.

### III. EVOLUTIONARY ALGORITHMS

Evolutionary algorithms belong to an algorithms class called Artificial Intelligence, which reproduce the phenomena observed in the nature in order to solve optimization problems. Among them we highlight the genetic algorithm [9-10]. This algorithm uses the specie evolution theory idea, where only the individuals that are more adaptable to the environment can survive, therefore are apt to reproduce themselves and to transmit their features to their descendants.

This type of algorithm can solve complex problems (with many variables, discontinued functions, complex derivatives, etc.), due to a probability method. This is an

algorithm that does not impose many limitations regarding the search for an optimal solution, since its sole reference is the fitness function or objective function. Below, we present some of the characteristics of the genetic algorithm used.

The proposed genetic algorithm starts with a population (a set of solutions) randomly generated, considering some parameters, such as minimal and maximum limits of market and price variable and the discretization of the decision variables. Population size is fixed and shall uniformly cover the search space in order to guarantee the algorithm performance. Each individual (potential solution) is represented by three chromosomes: (i) Chromosome A: contains information on the decision of participating or not in the auctions (binary codification), represented in Figure 3.

	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	
2007	1	1	1	1	1	1	1	1	1	1	A-1
2008	0	1	1	1	1	1	1	1	1	1	
2009	0	0	1	1	1	1	1	1	1	1	
2010	0	0	0	1	1	1	1	1	1	1	
2011	0	0	0	0	1	1	1	1	1	1	
2012	0	0	0	0	0	1	1	1	1	1	
2013	0	0	0	0	0	0	1	1	1	1	
2014	0	0	0	0	0	0	0	1	1	1	
2015	0	0	0	0	0	0	0	0	1	1	
2016	0	0	0	0	0	0	0	0	0	1	
2007	0	0	1	1	1	1	1	1	1	1	A-3
2008	0	0	0	1	1	1	1	1	1	1	
2009	0	0	0	0	1	1	1	1	1	1	
2010	0	0	0	0	0	1	1	1	1	1	
2011	0	0	0	0	0	0	1	1	1	1	
2012	0	0	0	0	0	0	0	1	1	1	
2013	0	0	0	0	0	0	0	0	1	1	
2014	0	0	0	0	0	0	0	0	0	1	
2007	0	0	0	0	1	1	1	1	1	1	A-5
2008	0	0	0	0	0	1	1	1	1	1	
2009	0	0	0	0	0	0	1	1	1	1	
2010	0	0	0	0	0	0	1	1	1	1	
2011	0	0	0	0	0	0	0	1	1	1	
2012	0	0	0	0	0	0	0	0	1	1	
2013	0	0	0	0	0	0	0	0	1	1	
2014	0	0	0	0	0	0	0	0	0	1	
2007	0	0	0	0	1	1	1	1	1	1	A-5
2008	0	0	0	0	0	1	1	1	1	1	
2009	0	0	0	0	0	0	1	1	1	1	
2010	0	0	0	0	0	0	1	1	1	1	
2011	0	0	0	0	0	0	0	1	1	1	
2012	0	0	0	0	0	0	0	0	1	1	
2013	0	0	0	0	0	0	0	0	0	1	
2014	0	0	0	0	0	0	0	0	0	1	

Figure 3 – Chromosome type A.

(ii) Chromosome B: contains energy price information for each auction during the study period. This chromosome is based on the analysis of final prices obtained in the auctions already placed (decimal codification), represented in Figure 4;

	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	
2007	RS/MWh	RS/MWh	RS/MWh	RS/MWh	RS/MWh	RS/MWh	RS/MWh	RS/MWh	RS/MWh	RS/MWh	A-1
2008	0	RS/MWh	RS/MWh	RS/MWh	RS/MWh	RS/MWh	RS/MWh	RS/MWh	RS/MWh	RS/MWh	
2009	0	0	RS/MWh	RS/MWh	RS/MWh	RS/MWh	RS/MWh	RS/MWh	RS/MWh	RS/MWh	
2010	0	0	0	RS/MWh	RS/MWh	RS/MWh	RS/MWh	RS/MWh	RS/MWh	RS/MWh	
2011	0	0	0	0	RS/MWh	RS/MWh	RS/MWh	RS/MWh	RS/MWh	RS/MWh	
2012	0	0	0	0	0	RS/MWh	RS/MWh	RS/MWh	RS/MWh	RS/MWh	
2013	0	0	0	0	0	0	RS/MWh	RS/MWh	RS/MWh	RS/MWh	
2014	0	0	0	0	0	0	0	RS/MWh	RS/MWh	RS/MWh	
2015	0	0	0	0	0	0	0	0	RS/MWh	RS/MWh	
2016	0	0	0	0	0	0	0	0	0	RS/MWh	
2007	0	0	0	RS/MWh	RS/MWh	RS/MWh	RS/MWh	RS/MWh	RS/MWh	RS/MWh	A-3
2008	0	0	0	RS/MWh	RS/MWh	RS/MWh	RS/MWh	RS/MWh	RS/MWh	RS/MWh	
2009	0	0	0	0	RS/MWh	RS/MWh	RS/MWh	RS/MWh	RS/MWh	RS/MWh	
2010	0	0	0	0	0	RS/MWh	RS/MWh	RS/MWh	RS/MWh	RS/MWh	
2011	0	0	0	0	0	0	RS/MWh	RS/MWh	RS/MWh	RS/MWh	
2012	0	0	0	0	0	0	0	RS/MWh	RS/MWh	RS/MWh	
2013	0	0	0	0	0	0	0	0	RS/MWh	RS/MWh	
2014	0	0	0	0	0	0	0	0	0	RS/MWh	
2007	0	0	0	0	RS/MWh	RS/MWh	RS/MWh	RS/MWh	RS/MWh	RS/MWh	A-5
2008	0	0	0	0	0	RS/MWh	RS/MWh	RS/MWh	RS/MWh	RS/MWh	
2009	0	0	0	0	0	0	RS/MWh	RS/MWh	RS/MWh	RS/MWh	
2010	0	0	0	0	0	0	0	RS/MWh	RS/MWh	RS/MWh	
2011	0	0	0	0	0	0	0	0	RS/MWh	RS/MWh	
2012	0	0	0	0	0	0	0	0	0	RS/MWh	

Figure 4 – Chromosome type B.

(iii) Chromosome C: contains the percentage of the company’s market to be contracted in each auction during the study period (decimal codification), as seen in Figure 5. We choose to work with the market percentage value due to the difficulty in obtaining data on the market for each distributor in order to perform a demand growth forecast.

Fitness Function (FF) aims at evaluating the potential of each individual related to the proposed target. Therefore, the FF of each individual (k) is based on the energy contracting total cost by the distributor during the ten years of the study. Contracting cost is obtained by the product among the three chromosomes that comprise the individual, chromosomes type A, B and C. This way, the one's fitness function is given by:

$$FF_k = A(0 - 1) \times B(R\$/MWh) \times C(MW) \quad (1)$$

	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017		
2007	% (MW)	% (MW)	% (MW)	% (MW)	% (MW)	% (MW)	% (MW)	% (MW)	% (MW)	% (MW)	A-1	
2008	0	% (MW)	% (MW)	% (MW)	% (MW)	% (MW)	% (MW)	% (MW)	% (MW)	% (MW)		
2009	0	0	% (MW)	% (MW)	% (MW)	% (MW)	% (MW)	% (MW)	% (MW)	% (MW)		
2010	0	0	0	% (MW)	% (MW)	% (MW)	% (MW)	% (MW)	% (MW)	% (MW)		
2011	0	0	0	0	% (MW)	% (MW)	% (MW)	% (MW)	% (MW)	% (MW)		
2012	0	0	0	0	0	% (MW)	% (MW)	% (MW)	% (MW)	% (MW)		
2013	0	0	0	0	0	0	% (MW)	% (MW)	% (MW)	% (MW)		
2014	0	0	0	0	0	0	0	% (MW)	% (MW)	% (MW)		
2015	0	0	0	0	0	0	0	0	% (MW)	% (MW)		
2016	0	0	0	0	0	0	0	0	0	% (MW)		
2007	0	0	% (MW)	% (MW)	% (MW)	% (MW)	% (MW)	% (MW)	% (MW)	% (MW)	A-3	
2008	0	0	0	% (MW)	% (MW)	% (MW)	% (MW)	% (MW)	% (MW)	% (MW)		
2009	0	0	0	0	% (MW)	% (MW)	% (MW)	% (MW)	% (MW)	% (MW)		
2010	0	0	0	0	0	% (MW)	% (MW)	% (MW)	% (MW)	% (MW)		
2011	0	0	0	0	0	0	% (MW)	% (MW)	% (MW)	% (MW)		
2012	0	0	0	0	0	0	0	% (MW)	% (MW)	% (MW)		
2013	0	0	0	0	0	0	0	0	% (MW)	% (MW)		
2014	0	0	0	0	0	0	0	0	0	% (MW)		
2007	0	0	0	0	% (MW)	% (MW)	% (MW)	% (MW)	% (MW)	% (MW)		A-5
2008	0	0	0	0	0	% (MW)	% (MW)	% (MW)	% (MW)	% (MW)		
2009	0	0	0	0	0	0	% (MW)	% (MW)	% (MW)	% (MW)		
2010	0	0	0	0	0	0	0	% (MW)	% (MW)	% (MW)		
2011	0	0	0	0	0	0	0	0	% (MW)	% (MW)		
2012	0	0	0	0	0	0	0	0	0	% (MW)		

Figure 5 – Chromosome type C.

As the objective is to determine the contracting optimal decisions in order to minimize the contracting total cost by the distributor and ensure that the market will be met, the final solution will correspond to the individual that presents the lower value for the fitness function. As genetic algorithm is originally developed to obtain global maximums, therefore, for the minimization problems like the one presented in this article, the fitness value needs to be inverted.

Genetic operators are responsible for the optimization process comprised by the specie selection and diversification during several generations. Operators make the more capable individuals (in this case, lower contracting costs) have a greater crossover probability, therefore conserving their adaptation features to their descendants, consequently, the individuals with low adaptability (in this case, higher contracting costs) are lost during the generations. This diversification provides the individuals to be better adapted to their environment and, therefore, reach a population with optimum or almost optimum fitness values. Genetic operators are divided in: (i) selection; (ii) cross over; (iii) mutation.

Selection operator aims at selecting the most adapted individuals to the environment in order to suffer the action from mutation and crossover operators and, consequently, generate a population more adapted to its ecologic niche. Therefore, the future generations will have a lower probability of being extinct. In this work, we choose to make the selection through stochastic sample.

Stochastic sample selection is similar to the casino roulette. The process is placed by the evaluation of each individual through adaptability (fitness function). After this evaluation, the fitness values are calculated and used to set

the roulette with proportional area. We spin this roulette with the same number that the population size is. With that the individuals that have the most adaptability skills have the higher chance of being selected for reproduction.

Crossover operator aims at performing the exchange of genetic material of the progenitors chosen by the selection operator. This way, their descendants will inherit a part of the features of one progenitor and another part from the other. So, the features of the more adapted progenitors will be conserved from generation to generation by their descendants, making them to adapt themselves best to the environment were they live. This operator is performed in one fixed number of individuals regulated by the crossover rate. In this work we choose the crossover at one outline.

In this type of crossover, progenitors' chromosomes are divided in two parts through a single outline, which was chosen randomly and is valid for all chromosomes. Figures 6 and 7 present the outline, the dark line highlighted, for a certain chromosome, for instance, referring to the decisions to participate or not in the auctions, of two progenitors.

	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	
2007											A-1
2008											
2009											
2010											
2011											
2012											
2013											
2014											
2015											
2016											
2007											A-3
2008											
2009											
2010											
2011											
2012											
2013											
2014											
2007											A-5
2008											
2009											
2010											
2011											
2012											

Figure 6 – Progenitor 1

	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	
2007											A-1
2008											
2009											
2010											
2011											
2012											
2013											
2014											
2015											
2016											
2007											A-3
2008											
2009											
2010											
2011											
2012											
2013											
2014											
2007											A-5
2008											
2009											
2010											
2011											
2012											

Figure 7 – Progenitor 2

After determining the outline, the genetic material is traded between the progenitors. It is important to mention that the outline is chosen randomly for each crossover performed during the optimization process. Therefore, the descendants will be formed by alternated "pieces" of their progenitors' chromosomes. Figures 8 and 9 illustrate the new descendants generated by the cross over.

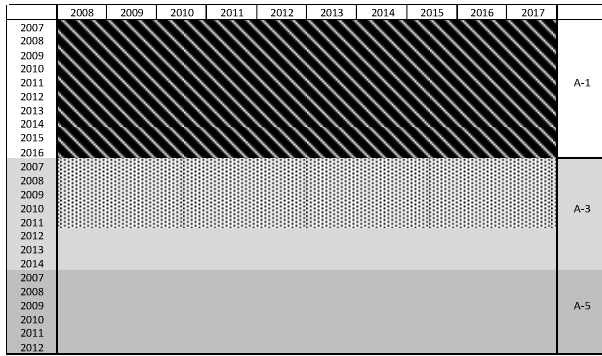


Figure 8 – Descendant 1

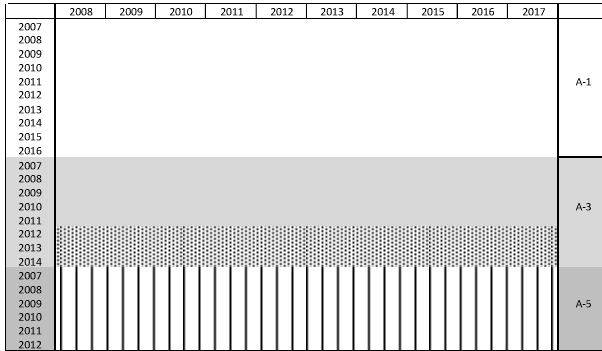


Figure 9 – Descendant 2

Regarding the chromosomes referring to the distributor contracting percentage, accordingly with the adopted proceeding, for the crossing between the progenitors, a non desired situation can occur: the chromosome type C of the new individual can not ensure the distributor annual contracting interval, which is from 100% to 103% of its market. In order to overcome this situation we use Method of Minor Adjustments (MMA) [11]. This technique aims at decreasing (in case of excess) or increasing (in case of lack) of the DISTCO annual contracting, in order to overcome this situation of subcontracting (<100%) or overcontracting (>103%). Regarding the chromosomes related to the energy prices in the auctions, chromosome B, a process was adopted which is similar to the chromosome type A, that is, the genetic material trade after the cutline.

The mutation operator aims at inserting new features to the descendants, and also restores the lost features of a certain generation. The process makes some descendants of each generation, ruled by a fixed percentage named mutation rate, suffer from a trade on the value of their genes. Gene position is selected randomly. Among the several types of mutation, we used a mutation based in trade, where two cutlines are randomly chosen and between them new values are picked, which form the final individual. This allows new solution region points to be visited. However, we emphasize the possibility of using the small adjustment methods for eventual sub or overcontracting that may occur.

The proposed genetic algorithm uses a concept introduced by Kenneth de Jong, the elitism. This concept

suggests that the best solution of a certain generation is not lost due to a possible not selection to reproduction. Therefore, at each generation, the best individual (best solution) can be selected or not for reproduction, and starts automatically to be part of the next generation until a better individual is found. Figure 10 presents the flowchart for the proposed genetic algorithm.

#### IV. CASE STUDY

In order to illustrate the results obtained by the proposed genetic algorithm, the following situations were considered: (i) 10-year analysis period (2007-2017); (ii) minimal interval (100% of market) and maximum interval (103% of market) of annual contracting by the DISTCO.

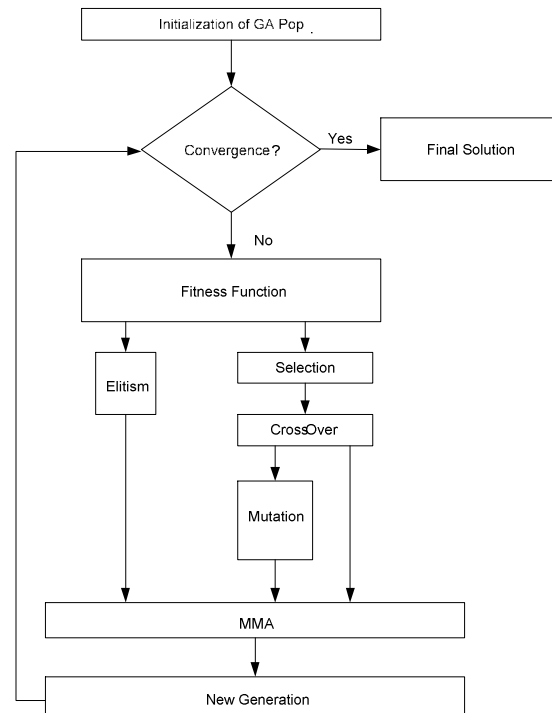


Figure 10 – Genetic Algorithm Flowchart

Regarding the evolutionary algorithm, the following features and values were adopted for the genetic parameters: (i) Population formed by 300 individuals; (ii) 100 generations; (iii) Crossover rate of 90% of the population; (iv) mutation rate of 5%; (v) random population initialization, but with boundaries well established for prices and market; (vi) convergence determined by the maximum number of iterations; (vii) elitism. It is important to accent that the values above mentioned were the ones that presented the best results among the set of tests performed.

#### Case 1- Analysis Based on Auction History

For this first simulation, we considered: (i) market growth of 5% per year [12]; (ii) the percentage already contracted in previous auctions (already existent contracting portfolio) in 2008; (iii) history price of auctions type A-1,

A-3 and A-5 already performed, as illustrated in Figure 2. However, only the values after the second semester of 2005 were used, since previous values refer to the mega auction, an auction with different rules performed in order to present a smooth transition between the old and new Brazilian energy market, which presents atypical values.

According to the history, the following price values occur: (i) auction A-1, variations up to  $\pm 4.45\%$ ; (ii) auction A-3, variations up to  $\pm 13.97\%$ ; (iii) auction A-5, variations up to  $\pm 15.85\%$ . Those variations were used to generate chromosome type B, related to the auction price, in which the price for 2008 is known (since the analysis is after 2007) and for the other years, new prices were generated based on the variations presented by the history concerning the final prices of 2008. Figure 11 presents the market percentage to be contracted based on a forecasted growth of 5% per year.

Figure 12 presents the convergence graphic of the genetic algorithm for the first simulation, in which a reduction of 11% can be realized regarding the best solution obtained in the first generation. That is, the starting point was a total contracting cost of R\$ 28.500,00 (best solution among the first one hundred generated solutions) and the final cost reached was R\$ 25.375,00 (last generation).

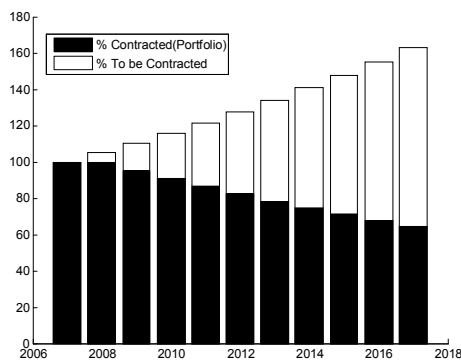


Figure 11 – Market Growth

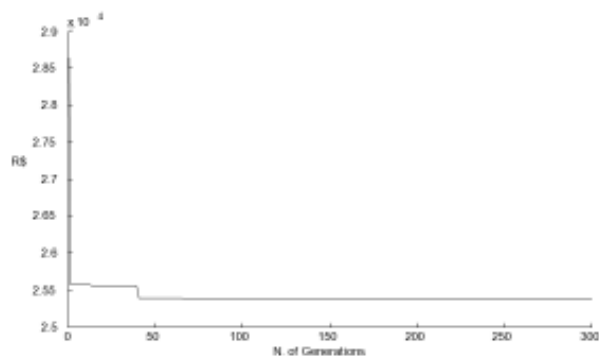


Figure 12 – Algorithm Convergence.

Regarding the contracting decisions, Figure 13 presents the graphic of optimal contracting percentage found by the evolutionary algorithm. The indication that the best strategy is to contract the major part of distributor market at

auction A-1, followed by the auctions A-3 and A-5, respectively.

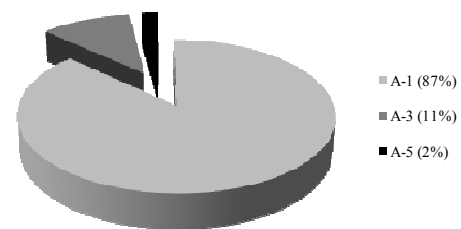


Figure 13 – Optimal Contracting Portfolio

Thus, as in the majority of the works involving evolutionary algorithms, it was chosen to perform new simulations and then to calculate the average, using it as indication of the final solution. Table 1 presents the final average obtained for the thirty simulations performed.

TABLE I – Average of Simulations Performed.

Cost (R\$)	A-1(%)	A-3(%)	A-5(%)
25.467,43	93.10	4.57	2.33

Considering the results reached, we conclude that, accordingly with the prices forecast based on price variations at previous auctions, the best contracting strategy for the distributor is to contract the average of 93% of market at the auction A-1, 5% at auction A-3 and 2% at auction A-5.

## Case 2- Exogenous Variables in Analysis

For this second simulation, it shall consider, as the previous case considered, price history of auctions type A-1, A-3 and A-5, performed from 2004 to 2008, and the respective price variations. However, we will also simulate an economic crisis starting in 2011 and finishing in late 2013. In order to do so, the energy price will have, initially, a strong trend of increasing, presenting atypical values, mainly for the existing energy auction (variations up to +30%) being amortized until that, in 2014, the year in which the values of energy price return to vary within the normal variation rate. The objective of this study is to verify which shall be the optimal strategy before an economic crisis and which shall be the impact during the years.

For the second simulation, the evolutionary algorithm stated from a total contracting cost of R\$ 35.000,00 (best solution among the first one hundred generated solutions) and reached a final cost of R\$ 26.096,00 (last generation). That is, a reduction of 25%, approximately.

Regarding the contracting decision, Figure 14 presents the graphic of the contracting percentage found by the genetic algorithm. Comparing it to the first simulation, due to the economic crisis, the contracting percentage at A-3

become important before crisis symptoms, price increase in 2011, and this can reflect in 2014 (A-3) and 2016 (A-5). See Figure 15.

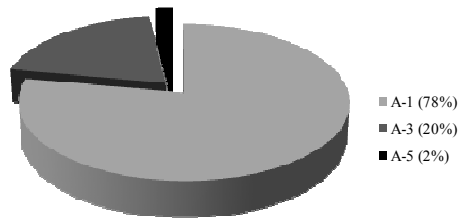


Figure 14 – Optimal Contracting Portfolio

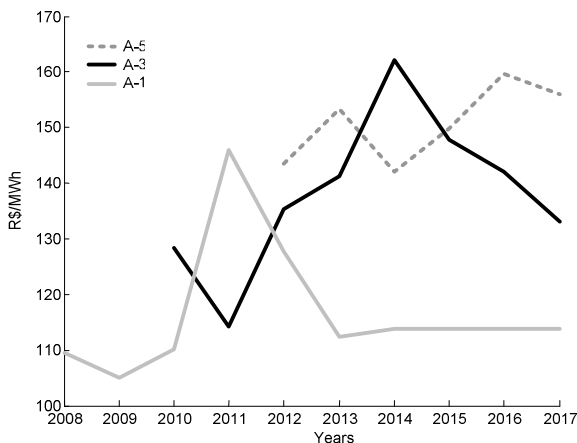


Figure 15 – Energy Price Variations.

Similar to the previous simulation, it was chosen to perform a set of simulations and then to calculate the results average, using it as indication of the final solution for the analyzed case. Table 2 presents the final average obtained for the thirty simulations performed.

TABLE II – Average of Performed Simulations.

Cost (R\$)	A-1(%)	A-3(%)	A-5(%)
26.432,87	82.03	15.19	2.78

## V. CONCLUSIONS

In this work, we developed a computer application based on evolutionary algorithms in order to obtain an optimal contracting portfolio by the DISTCOS. In order to do so, we analyzed energy auctions results in Brazil, from 2004 to 2008, aiming at providing information for the application development. Results indicate a strong trend for contracting at existing energy auctions followed by the contracting of new energy A-3 and A-5, respectively. We emphasize that, before a disturbing factor, as the increase of the price realized at the second simulation, the contracting at auction A-1 can have its share reduced at the contracting percentage, increasing the space for contracting new energy.

The results presented aim at pointing indications for the distributors concerning contracting decisions based on auctions already placed. This is due to the fact that the auction practices, for the domestic energy market, has been implemented recently, and it is not possible to obtain a volume of significant data, for instance, in order to get a price forecast through forecast classic models. To this fact, we add a complication factor of having several variables involved in the decision-making process, and the major part of information is not of public domain.

## VI. Future Works

Some possible future developments are described as follows:

- Expansion of analysis period from ten to fifteen years, which will affect the entire contracting period of auctions A-5.
- The possibility of making a distributor market forecast;
- Limit contracting percentages by DISTCOS according to the commercialization rules.
- Perform an analysis which considers the competition of the generating agents (evolutionary games), given the commercialization possibility at the short-term market.

## REFERENCES

- [1] Araújo, J. L. R. H.; "The case of Brasil: Reform by trial and error?" in Sioshansi, F.; Pfaffenberger, W.; Electricity Market Reform, Elsevier, 2006.
- [2] Pinto, L.; Dias, B., Szczupak, J., Maia, R., Tsunehiro, L.; "A Novel Risk Management Model Based on the Real Options Concept" in IEEE PES PowerTech, 2007.
- [3] Milgrom, P. Putting Auction Theory to Work. Cambridge, 2003.
- [4] Klemperer, P. Auctions: Theory and Practice. Princeton University Press, 2004.
- [5] Krishna, V. Auction Theory. Elsevier, 2002.
- [6] Chamber of Electrical Energy Commercialization (in Portuguese, CCEE), www.ccee.org.br.
- [7] Dias, B. H.; Pinto, L. M. V. G.; Szczupak, J.; "A Novel Model for the Optimum Energy Portfolio: Combining Stochastic Programming and Real Options Concepts", International Conference on Operational research for Development – ICORD, Brazil, 2007.
- [8] Reeves, C. R.; Rowe, J.E. Genetic Algorithms: Principles and perspectives: a Guide to GA Theory. Kluwer Academic Publishers, 2003.
- [9] Xu, J.; Luh, P. B.; White, F. B.; Ni, E.; Kasiviswanathan, K.; "Power Portfolio Optimization in Deregulated Electricity Markets with Risk Management"; IEEE Trans. Power System; vol. 21, No. 4, 2006.
- [10] Michalewicz, Z.; "Genetic Algorithms + Data Structures = Evolution Programs", Springer-Verlag, 3<sup>rd</sup> edition, 1994.
- [11] Marcato, A.; Oliveira, E. J.; Garcia, P. A. N.; Pereira, J. L. R.; Silva JR, I. C. da; Iung, A. M.; Mendes, A. G.; "Genetic Algorithm Approach Applied to LongTerm Generation Expansion Planning", IEEE Latin America Transmission and Distribution Conference and Exposition, 2006.
- [12] Energy Research Enterprise (EPE – in portuguese); Electrical Energy Market 2006-2015, 2005.