THE INFLUENCE OF OPERATIONAL MARGINAL COST SIMULATION METHODS ON ELECTRICITY CONTRACT PORTFOLIO STRATEGIES IN BRAZIL

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***Abstract*— The electricity price has been one of the most important variables since the introduction of deregulation on the electricity sector. On this way, efficient forecasting methods of spot prices have become crucial to maximize the agent benefits. In Brazil the electricity price is based on the operational marginal cost (OMC) provided by an optimization software (NEWAVE). Forecasting the OMC and its volatility has been one big problem in the Brazilian market because of the computational time taken by this software. Most of the traders in Brazil use the future OMCs given by the NEWAVE simulation to establish the electricity contract portfolio strategies, which is not corrected. At the end of the simulation process, the program provides the OMC trajectories along five years ahead based on 2000 synthetic inflow time series. These trajectories are far from the actual computation of the electricity spot prices. Actually, each month, the NEWAVE simulation is made by the Independent System Operator to set the prices of the next month and all the input variables are updated. Therefore, using the future OMCs of just one run of NEWAVE does not consider the stochastic nature of the other input variables and does not represent the actual procedure for calculating the Brazilian spot prices. As a result, only the OMCs of the first month are used to set the spot prices. This problem is highlighted in this paper using as a counter example with a fast and efficient model to simulate the OMC, which was built in a previous work using DOE (Design of Experiments) and ANN (Artificial Neural Networks). The analysis is made using some portfolio metrics like the *VaR*, *CVaR*, etc.**

***Index Terms*— Electricity Prices, Simulation, Design of Experiments and Artificial Neural Networks**

I. Introduction

During the two last decades many transformations occurred on the electrical power systems in many countries around the world. The main objective is to introduce market mechanisms in this field. The figure of the electricity market has emerged with the introduction of deregulation on the electricity sector, which has turned the electricity price one of the most important variables. Actually, the basic objective of deregulation consists in maximizing the efficiency in electricity generation and transmission in order to reduce the electricity prices. In this way, generators and consumers need precise future price information to establish their bidding strategies to maximize their benefits.

In Brazil, the power system restructuring process introduced new agents, such as: the National Regulatory Agency (ANEEL), the Independent System Operator (ONS), the Wholesale Electricity Market (CCEE) and the Energy Planning Institution (EPE). More recently it was enacted in 2004 the Law 10848 that established new rules for the Brazilian Wholesale Market. One of the major changes was the introduction of two trade environment: Regulated trade environment (RTE) and Free trade environment (FTE). The regulated trade was designed to the captive consumers that are represented by the distribution companies. The ANEEL and CCEE conduct buying auctions in a centralized way on behalf of the distribution companies.

The prices at FTE named MCP (Market Clearing Prices) are set by the marginal cost of the energy derived from the optimization program (NEWAVE) [1-2]. The MCP is the basis for the bilateral contracts at the FTE and for the auction bids at RTE because the contracted differences on both markets are priced by MCP.

As mentioned before, the electricity price is defined by the OMC (Operation Marginal Cost) derived from NEWAVE. This procedure significantly differs from most of other electricity markets around the world. This special market structure was designed because of the great portion of hydro generation in Brazil, corresponding to 90% of the total electricity generation. NEWAVE provides the OMC as the Lagrange coefficient of the load balance constraint. The objective function inside NEWAVE is to minimize the operational cost of the entire system considering the operation of the power plant reservoirs. A stochastic dynamic dual programming is used because present decisions affect the future costs and the overall optimization. The stochastic is introduced by just one variable, that is, the water inflows at the reservoirs. The other input variables are considered as deterministic variables like load demand, the schedule of new hydro and thermal plants, costs of fuels, and so on.

Most of the agents in Brazil use the future OMCs given by the NEWAVE simulation to establish the electricity contract portfolio strategies, which is not corrected. Among the outputs of this program are the OMC trajectories along five years ahead based on 2000 synthetic inflow time series. There are significant differences between these trajectories and the actual computation of the electricity spot prices. Each month the NEWAVE simulation is made and all the input variables are updated. As a result, only the OMCs of the first month are used to set the spot prices. Therefore, using the future OMCs of just one run of NEWAVE does not consider the stochastic of the other input variables and does not represent the actual procedure for calculating the spot prices.

One big problem in incorporating all the uncertainties is that NEWAVE is a time consuming computer program which usually takes four hours long (in a Pentium IV, 2 GHz with 2 Gbyte of memory). In [3], it was built a clone for this program using Design of Experiments (DOE) [4,5] and Artificial Neural Networks (ANN) techniques [6,7] in order to overcome this problem. Many tools regarding portfolio risk and return analysis use Monte Carlo Simulation (MCS), which implies in the Brazilian case a great number of NEWAVE simulations. Therefore, the utilization of the "clone" becomes essential to build a better contract portfolio.

This paper will compare the two approaches of simulating the future trajectories of spot prices: using just one run of NEWAVE and using the ANN Predictor to simulate many runs of this computer program. These approaches will be tested with energy selling and purchasing contracts using risk metrics like *VaR, CFaR, CVaR, PVaR* and others. Interesting conclusions about the current practice in Brazil are derived from this comparison.

II. ELECTRICITY PRICE FORECASTING

Since the beginning of the power system deregulation processes many methods and techniques have been developed to forecast the electricity price in competitive environments. An important work classifies and compares different techniques presented in [6]. Models using Time Series techniques were applied in many countries to predict the electricity price behavior [7]; stochastic process using demand and seasonality characteristics was used for the same purpose [8]; ANN models using different structures were applied to forecast electricity prices [9-10] and demand in some cases [11]; simulation models using load flow, optimal dispatch, energy optimization were used for precisely represent the power system operation [12-13].

The Brazilian system has four different and interconnected submarkets representing the country regions (Southeast, South, Northeast and North). There are also distinct types of thermal plants that use different fuels (Natural Gas, Diesel, Oil and Coal). The OMC is calculated by the optimization program NEWAVE, which establishes the economic dispatches with a joined representation of the hydro and thermal plants. The optimization is based on a SDDP method (Stochastic Dynamic Dual Programming).

The Brazilian electrical power system has many hydro generation plants and other particulars features. for the NEWAVE program is large. In the previous work [18] it was selected the most important variables that influence directly the electricity price..The number of these input variables used to build the NEWAVE "clone" reaches twenty seven. Changes on these input variables produce great impacts on the final OMC. Besides the OMC, other NEWAVE output variables are included in the model: final energy storage, hydro generation and energy deficit risks. The total number of output variables treated in this process reaches 32, but only the OMC outputs are .used in this paper.

An analysis about the impact of the input variables on the OMC was made in [18]. In the analysis the DOE techniques was used for identifying the principal input variables. These variables are: demand of energy; load growth rate; reservoir bulk storage; inflow energy; thermal generation fuel costs; thermal plants unavailability; thermal and hydro plants expansion plan. Figure 1 shows the main variables. Although the diffusion of DOE methodology is new, commercial software like MINITAB [16] and STATISTICA [17] has added it and so its utilization has increased.

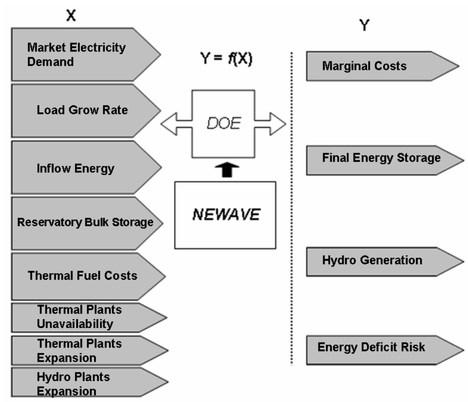

Figure 1 Design of Experiments applied to NEWAVE

The objective was to use the principal variables to create a set of NEWAVE runs denominated as the training sample in order to build a model using ANN. At the end of this DOE process, a final sample to the ANN training was represented by 328 cases (36 cases of the First DOE, 36 of the second and 256 of the last one).

An ANN is a "machine" created with the intention of modeling a procedure that is realized by the human brain when it develops a specific function. Some important characteristics of ANN are: learning from examples, adaptation to new situations, robustness, generalization about new examples, fast solutions without much process information, solution of complex multivariate functions, computational efficiency, and possibility of work in real time. Because of these characteristics the applications of ANN are vast like: pattern recognition, data classification, forecast, process control, functions approach, credit valuation and others.

An ANN has two important elements, the architecture and the learning algorithm. In [18], the training process was done using the software STATISTICA with the Intelligent Problem Solver (IPS). The IPS is an easy tool with a great analysis power that guides the user in a process which begins with the construction of different types of ANN and evolves into the selection of the network that has the best performance.

The Multilayer Perception (MLP) network was, in this case, superior to other types of ANN for the addressed problem. It was used three ANNs to build the NEWAVE clone with the back propagation learning algorithm. Figure 2 shows the final model architecture.

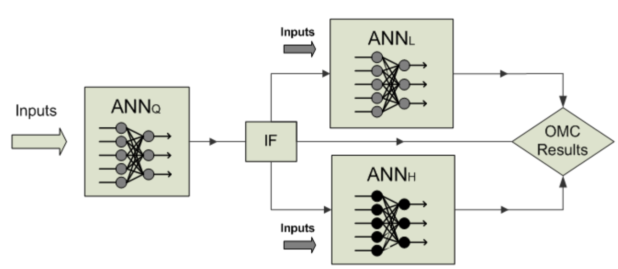

Figure 2: Final ANN architecture

The first ANN, the classification ANN (ANN$_C$), classifies the range of the OMC into low or high. The other two ANN's provide the OMC for high values (ANN$_H$) and for low values

(ANN_L). Table 1 gives the values of SD. Ratio, σ_S and σ_R for each ANN.

The first ANN has the classification function indicating which ANN (high or low) should be used. The adopted criterion for the response classification was the OMC median obtained from the results of the training step. If the OMC obtained from ANN_Q is in a range of + 10% or – 10% of the median value, the output response will be equal to the OMC obtained under the ANN_Q, i.e., it would not be necessary to use the other two ANNs.

For the NEWAVE simulations with a base case of 2006, the OMC median is 96.72 [US$/MW]. Therefore, if the ANN_C output stays below 87.04 [US$/MW] (median - 10%) the OMC will be simulated by ANN_L. Otherwise, if the output stays above the 106.39 [US$/MW] (median + 10%) the OMC will be simulated by ANN_H.

The set of ANNs produced can substitute the NEWAVE with advantages in terms of the computational effort. The deviations observed using the ANN simulator is not representative and do not compromise its use on a risk analysis algorithm, which is the main objective of this paper. More details about the construction of this predictor can be found in [18] and from now on this set of ANNs will be named as ANN Predictor.

III.RISK ASSESSMENT USING NEWAVE

A. Overview

For investment risk analysis there are a lot of approaches. As the cash flows are based on random variables, the risk assessment usually represents the deviation of an average return. The standard deviation of the net present value and the probability of a negative return are some examples of metrics that can be used for risk assessment [19].

The Value at Risk (*VaR*) is one of these metrics that presents the maximum loss of a portfolio for a given period of time and a confidence interval. The *VaR* measures the loss that can occur because of the market risk [20].

There are a lot of methods to assess the *VaR* based on historical information which can be divided into three groups:

- Historical simulation approach
- Monte Carlo Simulation
- Variance and co-variance method

In the historical simulation approach, a probabilistic distribution must be obtained based on a price series for a given period of time. At the same way, for the Monte Carlo Simulation (MCS), it can be used an empirical distribution of price time series. In MCS, price trajectories are generated following a statistical distribution. For the third method has a variety of methodologies but the most popular is the Autoregressive Conditional Heterocedasticity Models (ARCH) [21]. Figure 3 shows how the *VaR* is determined based on a return distribution function.

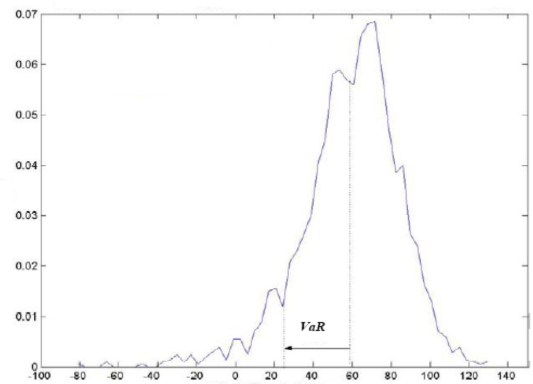

Figure 3: Return Distribution Function and *VaR*.

For the Brazilian electricity market, the price time series can be simulated using the results of NEWAVE. Based on these prices are built probabilistic cash flows where the risk metrics are calculated. As the goal is to find an optimal portfolio of contracts, a linear program approach is used with the objective of maximizing the return or minimizing the risk. In the latter case, the variance is not usually used because it would penalize the positive variance which is good for the investors. Therefore, only the negative variance is considered, which means returns below the average.

B. Simulation

Let $\boldsymbol{\pi}_{t,s} = \begin{vmatrix} \pi_{1,1} & \cdots & \pi_{t,1} \\ \cdots & \cdots & \cdots \\ \pi_{1,s} & \cdots & \pi_{t,s} \end{vmatrix}$ be the random variable which represents the spot price for each time period t=1,...,T for a set of spot price series s=1,...,S. The dispatch of the company at time t is $\boldsymbol{D}_t = (D_1,..,D_t)$, and the energy volume that may be traded through n bilateral contract candidates is $\boldsymbol{X}=(x_1,x_2,...,x_n)$. Besides, let $P=(P_1,...,P_n)$ be the energy price associated with the n bilateral contract candidates**.** *Cop* means the generation costs of plant, J_n is the time instant when the contract candidate n starts and K_n is the time instant when it ends. The net revenue of a generator for each time period t considering the price series s may be determined by Equation 1.

$$R_{t,s} = \sum_{\substack{i=1 \\ k_n \geq t \\ J_n \leq t}}^{n} \left(P_i - \pi_{t,s}\right)x_n + \left(\pi_{t,s} - COP\right)D_{t,s} \qquad \text{Eq 1}$$

As an example, a generation company has a contract portfolio defined at Table 1 and Figure 4 for a given period.

Table 1: Contract data

Contract	Submarket	Start (Month)	End (Month)	Price (R$/Mw)	Reservatory Bulk Storage (MW)
I1	SE/CO	01	12	85	294
I2	SE/CO	01	24	82,50	457
I3	SE/CO	01	48	98,20	150
I4	SE/CO	01	12	85	239
I5	SE/CO	01	24	76,60	74
I6	SE/CO	01	48	78,20	47

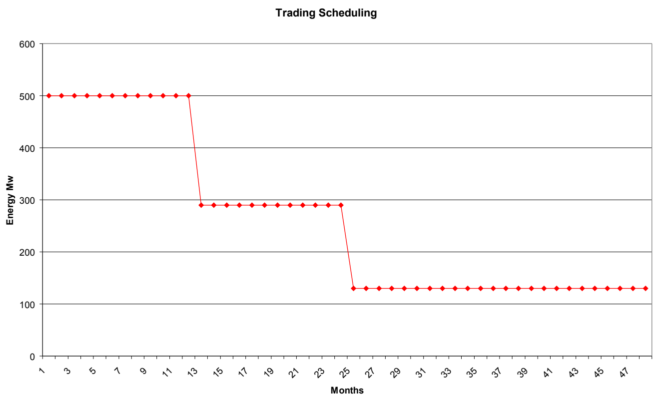

Figure 4: Trading strategy

From the table, the portfolio is described as follows: at the first month it was sold 210 MW for agent I1, 100 MW for agent I2, 50 MW for agent I3, 60 MW for agent I4, 50 MW for agent I5 and 30 MW for agent I6.

The cash flow calculation considering 2000 inflow series and 48 months is shown in Figure 5.

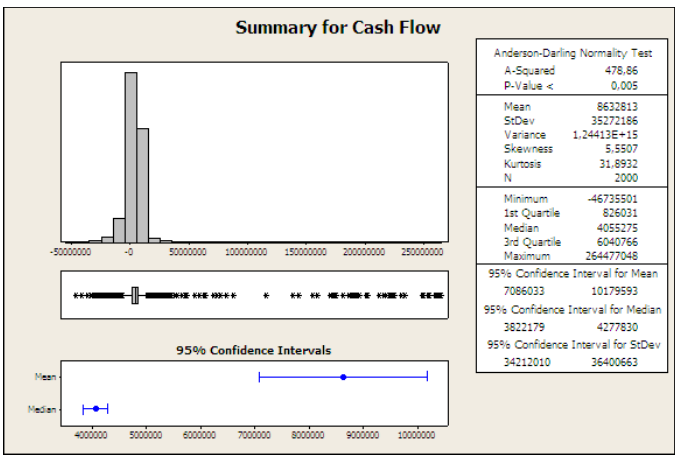

Figure 5 Portfolio Return

Based on the portfolio present values, it is possible to assess the *VaR* for a confidence interval of 95%. In this example, it was equal US$ 4.980 million which means that it is expected a loss of this value for an average return of US$ 4.316 million.

IV. RISK ASSESSMENT USING THE ANN PREDICTOR

A. Overview

In the previous process the NEWAVE was performed to create the spot price trajectories. In these trajectories it was assumed no uncertainty in terms of load demand, generation capacity add-ins, fuel costs, and so on. Only the water inflows at reservoirs were treated as a random variable. Using the ANN Predictor described in section II, it is possible to include all the most relevant source of risk for the contract portfolios. Figure 6 presents the relation of OMC prediction with the risk assessment.

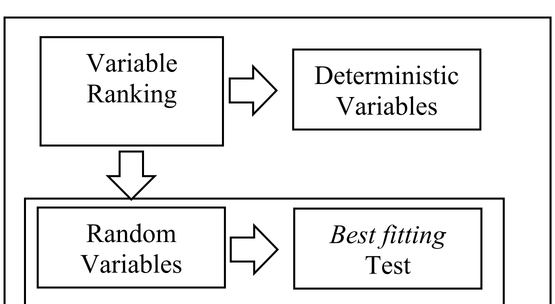

Figure 6: Defining OMC using the ANN Predictor.

Firstly, it is necessary to classify the deterministic and the stochastic variables to feed the ANN Predictor.

The independent variables *Sub1, Sub2, Sub3* and *Sub4* are the initial load for the Southeast, South, North and Northeast sub-markets respectively. The variable *TxM* is the overall annual load growth rate. The *VEaf1, VEaf2, VEaf3* and *VEaf4* are the energy associated to the water inflows to the equivalent reservoirs of each submarket. The initial reservoir volume is another important variable and is represented by *ReSub1, ReSub2, ReSub3* and *ReSub4* in each submarket. The reservoir volume is the variable that links the operation of one month to the subsequent month, i.e., there is a temporal dependence between the volumes of each submarket in each month. Based on the approach adopted by the Brazilian ISO in terms of the hydrothermal coordination, i.e., a horizon of 5 years and a step of one month, the initial volume for each step vary according to the operation decision of the previous months, which creates a temporal dependence among the months.

Although the fuel costs, generation capacity add-ins and thermal plant outages may vary during the time period analysis, in this first study it was considered deterministic. Further work will deal with the uncertainties of these variables.

Since there is a set of independent variables that influence on the dependent variable OMC, an useful tool to define the OMC distribution is the Monte Carlo Simulation (MSC). The MCS approach consists in assigning a pattern probability distribution (as for instance, the normal, the lognormal, the Weibull, etc.) for each random independent variable. In case it's not possible to define a pattern distribution, an empirical distribution of this variable can be used, based on the historical data assumed.

After the distributions for the random independent variables are defined, a random walk is run on each distribution of the independent variables, which are combined generating one scenario. By repeating this process, it is gotten a certain number of scenarios (for this case, two thousand scenarios were generated) and the distribution function for the dependent variable, i.e., the OMC [22].

After defining which are the random variables and which are the deterministic variables, the next step consists in establishing the behavior of the random variable, that is, to perform the best fitting of the data and check to which pattern distribution the data suits better. Figure 7 presents the results for variable *Sub1*. The test gives two parameters AD (Anderson Darling) and the p-value. Thus, the distribution that suits better the data is the one that gives the lower *AD* and the higher *p-value*. For this case, the 3-parameter Weibull distribution function was chosen.

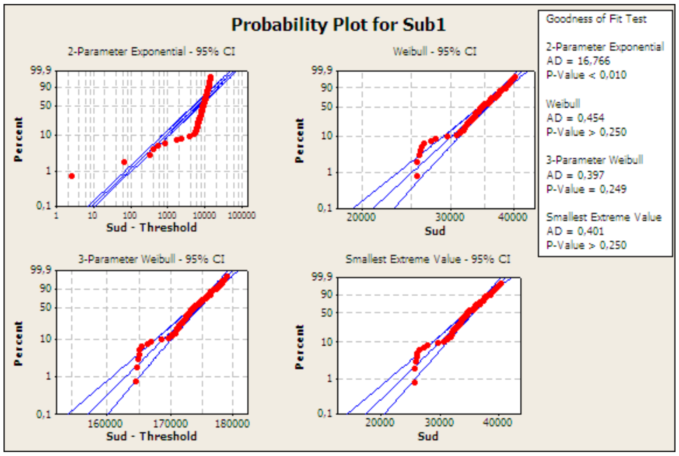

Figure 7: Best fitting to Sub1

Based on the MCS, the input variables are set and the ANN Predictor is used for providing the outputs. In other words, the randomness of the input variables is considered and it is possible to define a set of trajectories for the submarket OMCs. Using this approach, the actual process of determining the spot prices is better represented comparing with the use of NEWAVE alone.

From the distributions it's possible to define the scenarios. For example, Figure 8 presents one scenario being processed by the ANN Predictor.

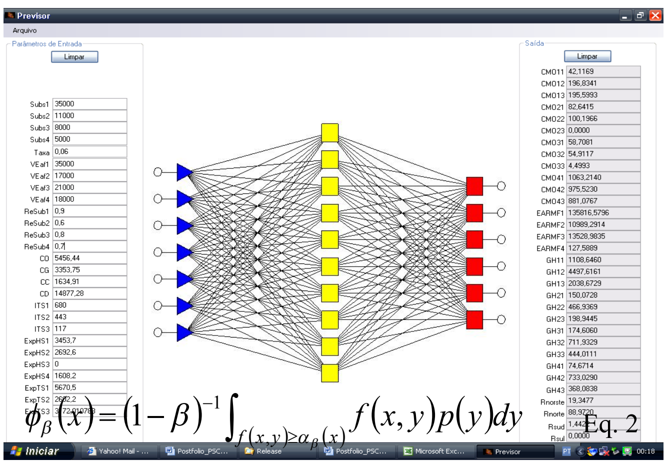

Figure 8: The ANN Predictor

B. Results

The Company cash flow distribution obtained for the two thousand scenarios generated from the Monte Carlo simulation applied to ANN Predictor is shown in Figure 9. It was used the same amount of iterations as for the NEWAVE simulation alone just for comparing purposes. However it is advisable to increase this number.

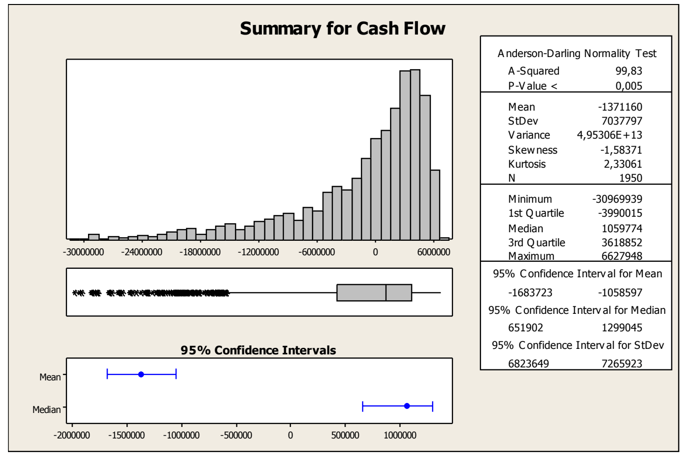

Figure 9: Portfolio return

Through the distribution of the present values of the portfolio, the *VaR* can be determined using a confidence interval of 95% and it is equal to US$ 5.989 millions. Therefore, under normal market conditions, a loss equal or higher than US$ 5.989 millions can be expected every twenty-four months with an average negative return of US$ 685 thousands. Comparing with the values obtained without using the ANN Predictor we have a greater *VaR* and a lower average return. This results indicates that when the uncertainty of variables such as electricity load and offer is included in the analysis, the risk tends to increase and the portfolio returns tend to decrease.

Although the *VaR* gives information about the expected loss for a fixed period of time under normal market conditions, the loss higher than the VaR to which the Company is subjected is not known. The *Conditional Value at Risk - CVaR* tool is another metric that gives the loss that exceeds the *VaR*. Beyond that, the *CvaR* is a risk measurement more coherent than the *VaR* and more details about the *CVaR* can be found in [23]. The *CVaR* of a return distribution with a significance level $\boldsymbol{\beta}$, being $\alpha_\beta(x)$ the *VaR*, *f(x,y)* the return function, *p(y)* the probability density induced by the uncertainties of variable *y*, in this case the uncertainties about the spot prices, can be defined by Equation 2.

$$\phi_\beta(x) = (1-\beta)^{-1}\int_{f(x,y)\ge\alpha_\beta(x)} f(x,y)p(y)dy \qquad \text{Eq. 2}$$

In the equation 2, the probability that $f(x,y)\ge\alpha_\beta(x)$ is therefore equal to 1-β. Thus, $\Phi_\beta(x)$ comes out as the conditional expectation of the loss associated with *x* relative to the loss being $\alpha_\beta(x)$ or greater. In this way, it can be done a characterization of $\Phi_\beta(x)$ and $\alpha_\beta(x)$ in terms of the function F_β as in Equation 3.

$$F_\beta(x,\alpha) = \alpha + (1-\beta)^{-1}\int_{y\in R^m}\left[f(x,y)-\alpha\right]^+ p(y)dy \qquad \text{Eq. 3}$$

The *VaR* ($\alpha_\beta(x)$) may be obtained instead as a byproduct. Furthermore, the integral in Equation 3 can be approximated in various ways. As an example, this can be done by sampling the probability distribution of *y* according to its probability density *p(y)*. The sampling creates a collection of vectors y_k, where $k=1$ to q, the approximation of $F_\beta(x,\alpha)$ is given in Equation 4 [20].

$$F_{\beta}(x,\alpha) = \alpha + \frac{1}{q(1-\beta)}\sum_{k=1}^{q}\left[f(x,y_k)-\alpha\right] \quad \text{Eq. 4}$$

Table 2 presents the average return values, *VaR* and *CVaR*, for the portfolio return distribution with and without using the ANN Predictor.

Table 2: Results

	Newave (US$ million)	ANN Predictor (US$ million)
Average return	4.316	0.685
$VaR_{5\%}$	4.980	5.989
$CVaR_{5\%}$	9.370	7.365

Comparing the values of Table 4, it can be noticed that the *VaR* defined by the simulations with the ANN Predictor is really close to the *CVaR*, that is, an approximate difference of 23%. In another way, the relation between the *VaR* and the *CVaR* without the ANN Predictor is approximately 88%. This means that, when analyzing the portfolio by the ANN Predictor combined with the Monte Carlo simulation, all the important uncertainties related to the system variables are modeled and the loss, in market normal conditions, for a significant level of 5%, tends to reach the actual loss for what the portfolio is subjected. Therefore, using the ANN Predictor combined with the MCS method, the *VaR i*s closed to *CVaR*. This fact does not occur when only the inflow uncertainty is considered, i.e., the sole use of NEWAVE. …

V. CONCLUSION

A methodology using the ANN Predictor combined with the MCS has been proposed in this paper. The hydrothermal dispatch model inside NEWAVE does not consider other uncertainties besides the water inflows. The other variables such as the initial water volume at the reservoirs and the load growth have a great influence on the OMC and consequently on the electricity spot prices. One important characteristic of the ANN Predictor model is its fastness, being possible to execute a great number of scenarios (iterations) through the Monte Carlo method. The inclusion of these scenarios changes drastically the results on portfolio risk and return in comparison with the current approach using in Brazil.

The methodology proposed and exemplified in this paper can help on the establishment of a strategy for analysing portfolios of electrical energy contracts under the current electricity market rules in Brazil.

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BIOGRAPHY

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