Hybrid Approach for Energy Price Prediction in Brazilian Market

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***Abstract*—This paper proposes a hybrid approach for short-term energy price prediction. This approach combines a genetic algorithm (GA) that evolves individuals represented by a set of production rules, these rules are extracted from chromosomes and generate the genotypes, which are mapped to phenotypes(Deep Neural Networks). The Artificial Neural Networks (ANNs) are then trained and then validated, and the prediction tests are carried out. The genotypes are classified by the performances of their ANNs in prediction and the GA selects the best individuals for mutation and crossover operations, which provide a new population. The previous steps are repeated through n generations. The result is an optimized neural network architecture for energy price prediction. The results show good ability to predict spikes and satisfactory accuracy according to error measures, delivering an accurate prediction. Finally, the results are compared with traditional techniques.**

***Keywords*—NeuroEvolution; Genetic Algorithm; Neural Networks, Time series forecasting**

I. Introduction

During the 1990s, the Brazilian electricity regulatory model began to be restructured to promote competition in generation and trading activities and to the construction of efficient regulation in transmission and distribution activities, as well as to attract investment in the sector. The energy market reform has brought greater risks associated with energy procurement. The ”how much” and ”when” to buy on the spot market are crucial decisions for power companies. Because such decisions depend on the price of electricity, a misguided investment strategy today could cost millions of dollars in the future.

Predicting the price of electricity is an important issue for all market participants to decide on the most appropriate bidding strategies and to establish bilateral contracts that maximize their profits and minimize their risks. Energy prices typically exhibit seasonality, high volatility and spikes. In addition, the price of energy is influenced by many factors such as uncertainty of energy demand, climate, hydrology and fuel prices. The prediction of future values of the price of electricity and its peaks is of great importance for the decision making process and the elaboration of energy trading strategies [8].

Recently hybrid forecast methods with promising results have also proposed in the literature [8]. In this context, this paper test the possibilities of a hybrid system called Artificial Development and Evolution of Deep Neural Networks (ADEANN-Deep) for shor-term energy price prediction using explanatory variables. Our approach is inspired by two natural biological mechanisms: genetic encoding and the evolution of genetic coding [11].

The ADEANN-Deep integrates two components. The first is a generative representation that represents genotypes (a set of production rules of a L- System) by a compact IES. The IES also conducts and controls the process of mapping the genotypes to the phenotypes (complex neural network morphologies). To mimic the DNA encoding scheme and enable scalability, our IES leverages the phenotype representation to a smaller genotype. The second component is a genetic algorithm (GA), a simplified representation of natural evolution. In local search problems based on GAs, a bit string is called a chromosome (the genotype). Each bit on the chromosome is a gene, and a gene set represents the parameters of a function to be optimized. Each string is assigned a fitness that indicates the quality of its encoded solution (the phenotype). The general structure of ADEANN-Deep is shown in Fig.1. The hybrid system is described in detail in section V.

In relation to the previous version of ADEANN [11], this research presents the following improvements: system migration to Python language justified by its applicability and portability in the artificial intelligence area, which enabled integration with prominent frameworks used in the current market for data processing, like Pandas, and data science, like Keras and Tensorflow. This new version of the hybrid system (ADEANN-Deep) using Keras/Tensorflow has expanded the possibility of the system to use various deep and recurrent Neural Network architectures.

This paper is organized as follows. Section II discusses related work. Section III presents the features of the Brazilian electricity market. In Section IV we describe a new approach to formalize the problem of ADANNs (artificial development and evolution of ANNs) as a local search based on rational agents. Section V introduces a biologically inspired method for automatic design of ANNs. Section VI presents Material and Methods. Lastly, simulation results and conclusions are presented in Sections VII and VIII, respectively.

II. Related Work

The paper [1] used an evolutionary algorithm-based search engine and Backus Naur form notation to find symbolic expressions describing its application in the control function synthesis problem. They used feed-forward neural network as an approximation of the control function, which depends on the object state variables. A two-stage algorithm is presented: grammatical evolution optimizes neural network structure and genetic algorithm tunes weights. We performed the computational using the simple kinematic model of a two-wheel driving mobile robot.

The paper [2], have proposed a quantum-inspired stacked auto-encoder-based deep neural network (Q-DNN) learning algorithm. The proposed Q-DNN uses stacked auto-encoder to form a deep neural network. This quantum computing concept has been used to optimize the learning parameters of the algorithm. The proposed Q-DNN achieves promising results in terms of classification accuracy, sensitivity, and specificity in comparison with other approaches.

The paper [3], proposes a new hybrid approach for short-term energy price prediction. The approach combines auto-regressive integrated moving average (ARIMA) and neural network (NN) models in a cascaded structure and uses explanatory variables. A two step procedure is applied. In the first step, the selected explanatory variables are predicted. In the second one, the energy prices are forecasted by using the explanatory variables prediction.

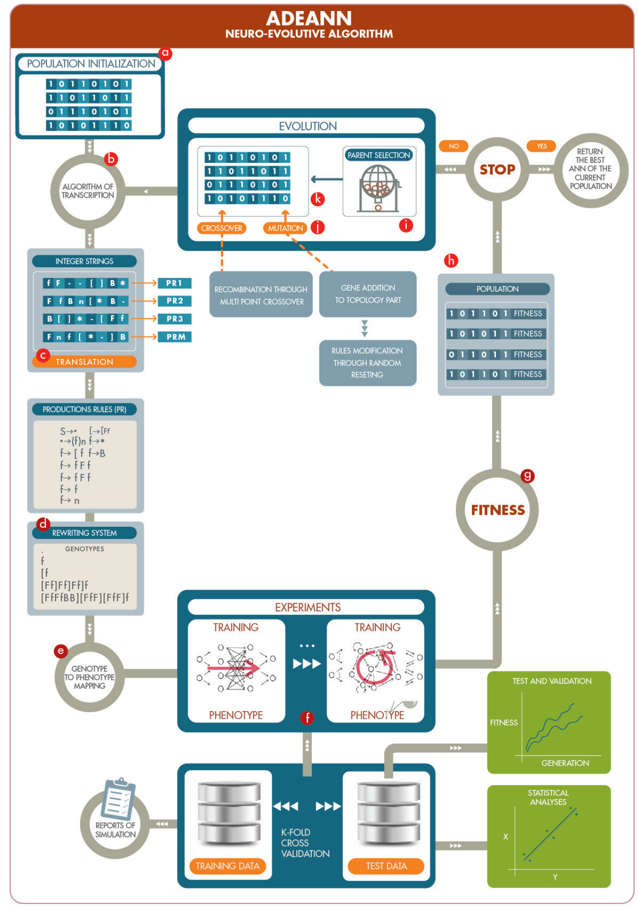

Fig. 1. The general structure of ADEANN-Deep.

III. Brazilian electricity market

The Brazilian energy market operates with two trading environments, one regulated and the other free. The former involves a pool of purchasing agents buying power from selling agents (generators, independent power producers or self-producers) in public auctions under set prices, while in the latter market buyers and sellers are free to establish bilateral contracts and negociate prices and conditions. The difference between the quantity of energy contracted and that effectively consumed or produced by the agents is accounted in the short-term market based on the spot price called PLD (settlement price for the differences) [3]. PLD is calculated weekly and is based on the system marginal cost of operation obtained from an optimization process to dispatch generators. The PLD is established by the Brazilian Electricity Regulatory Agency (ANEEL) and is evaluated to each submarket associated with the country regions: North, Northeast, Center-west/Southeast, and South.

Brazil uses a cost-based market instead of a bid-based market, and adopts a tight pool model with a centralized and least cost dispatch organized by National System Operator (ONS). This scheme is adopted due the country peculiarities, which has an installed capacity of 121 GW where 65.96 % corresponds to hydro generation. The hydro system is composed of several reservoirs capable of multi-year regulation located at the same river with differents owners [3].

IV. Outline of the Approach

Our approach involves the formulation of an artificial neural network design as an optimization problem (ANNDP), that is: given a set of L observations on the behavior of a particular process, Ψ=$\{(xd^l, yd^l)\}$, l = 1...L , where xd^l represents a numeric vector defined in R^n and yd^l is a numeric vector defined in R^m, the goal is to find an ANN's topology, yc^l = ANN(w*, xd^l), which minimizes the mean square error between yd^l and yc^l, this is, between the desired values in the observations set and the computed values in the neurons' outputs situated in the ANN's output layer.

An ANNs topology can be described as a finite set of neurons, that is, nodes of an oriented graph Nodes =$\{$n1, n2, ..nk$\}$, and a finite set H $\subseteq$ N x N of connections between neurons, which means directed edges in graphs notation. An input layer is a set of input units, that is, a subset of n nodes whereas an output layer is a set of output units, namely a subset of m nodes. In feed-forward ANNs(FANNs), the k^{th} layer (k $>$ 1) is the set of all nodes n_i ϵ Nodes . These types of nodes have an edge path of length k - 1 between some input unit and u. In fully connected recurrent ANNs (RANNs), all units have connections to all non-input units.

Function SEARCH−ANN(SearchParam, TransitionModel, FitnessFunction) **return** an ANN topology

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1:inputs: SearchParam, TransitionModel, FitnessFunction
2:vars: Pop, t, PopPerformances;
3:k← 0
4:$ANNsPop^k$←Generate-ANNs(SearchParam)
5:$ANNsPerformance$← Evaluate-ANNs($ANNsPop^k$, FitnessFunction)
6:loop do
7:if StopConditionTest(k, ANNsPerformance, SearchParam)
8:then return solution(Best-ANN($ANNsPop^k$, ANNsPerformance)
9:$ANNsPop^{(k+1)}$←($ANNsPop^{(k+1)}$, ANNsPerformance, TransitionModel, SearchParam)
10:ANNsPerformance←Evaluate-ANNs($ANNsPop^{(k+1)}$, FitnessFunction)
11:k ←k+1
12:end

We approach the solution of ANNDP based on the methodology of Russell and Norvig [12] called problem-solving-agent, whose agent is named ADEANN (Artificial Development and Evolution of ANNs), which encapsulates a special scheme of solutions representation as well as a local search strategy based on genetic algorithms to solve the problem. Regarding the representation scheme, the approach adopts a generative representation, which means that, instead of an encoded ANN topology, each chromosome stores a set of production rules of a Lindenmayer system, which, in turn, generates ANN's topologies regarding the solution process, the SEARCH-ANN function outlined below illustrates the structure of the program in the ADEANN agent.

The SEARCH-ANN function starts the local search process aiming at achieving an artificial neural network topology yc^l=ANN$\{(w^*, xd^l)\}$, which minimizes the mean square error between yd^l and yc^l, for 1 = 1...L in the ANNDPs formulation. This function employs information on the search parameters (SearchParam input term) as well as a transition model (TransitionModel input term) to describe how to modify current populations of ANNs and generate a new population, in addition to an evaluation function (FitnessFunction input term) to measure the value of each ANN in a current population.

Firstly, in the beginning of the process, Generate-ANNs function generates an initial population of ANNs, in which each ANN is represented by a set of production rules of a Lindenmayer system codified in a chromosome. This function considers the information in the SearchParam input term on

Rule Identifier	Rule
1,2	S→. (axiom) (2) .→(f...f)n
3	(3.1) f→[f (3.2) f→fFf (3.3) f→fF (3.4) f→n
3,4,5	(3.5) f→f (3.6) f→fB (4) [→[Ff] (5) f→f*

TABLE I
THE PRODUCTION RULES OF THE PARAMETRIC L-SYSTEM WITH MEMORY

the desired number of ANNs in the populations as well as on the desired length for the chromosomes in the population. Evaluate-ANNs function stores in ANNsPerformace the computed performance value of each ANN topology in the current population based on the mean square error computed in the output layer of the ANN-SEARCH-ANN function, which employs an iteration counter (k) and a condition named StopConditionTest boolean function to decide when to stop the local search process and return a solution to a problem. The description of the stop condition is based on a proposition relating the information on the current iteration counter k and the information available in the SearchParam input term. This means that the max number of loops in its repetition scheme is central to the local search strategy in the approach, as well as an ideal performance value such that for an ANN to be considered a solution. Modify-ANN function is executed repeatedly seeking to transform a current population of ANNs in a new population of ANNs. In our approach, this function encapsulates the evolutionary principles of pairs selection and crossing over pairs and individual mutation. Central to the approach, compact indirect encoding scheme (IES) conducts and controls the process of mapping a set of production rules of a Lindenmayer system codified in a chromosome to an associated ANN topology.

V. Biologically Inspired NEA

The optimization process of ADEANN-Deep proceeds through several stages. The GA starts with a population of individuals randomly initialized with 0s and 1s Fig. 1 a. Second , the bits of each individual of the population are subjected to transcription Fig. 1 b and translation Fig. 1 c, following valid production rules. Both processes are performed by the function Rule-Extraction-with-GA, presented in Section V.B. After finding the appropriate production rules (Table I), the rewriting system generates the genotypes Fig. 1 d. All of the genotypes are mapped to phenotypes (ANN architectures) Fig. 1 e. The ANNs are then trained Fig. 1 f and validated, and tests are carried out. The classification accuracy of each ANN is measured from its fitness Fig. 1 g. The genotypes are classified by the performances of their ANNs Fig. 1 h. The GA selects the best individuals Fig.1 i)for mutation and crossover operations Fig. 1 j, which provide the new population Fig. 1 k. The previous steps are repeated through n generations. The following subsections describe the three subsystems of ADEANN-Deep.

A. L-system based artificial embryogenesis model

To mimic the mechanism of grown structures, including neurons, we adopt a parametric L-system with memory. It

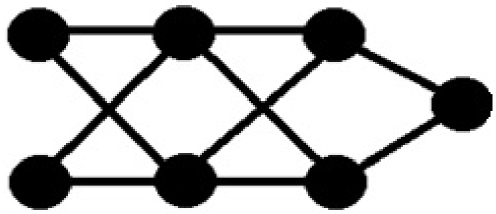

Fig. 2. A simple example of the construction process of a branch of an iterated ANN using the rules of the L-system is illustrated in Table I.

comprises a set of rules created from an alphabet. This system can be described as a grammar $G = \{\Sigma, \Pi, \alpha\}$, where the alphabet consists of the elements of the set $\Sigma = \{., f, F, n, [,], *, B\}$, and the production rules (Π) described in Table I. The axiom α = . is the starting point of the developmental process, where f denotes a neuron and F is a connection between neurons, [and] indicate storage and recovery, respectively, of the current state of the development, * denotes that the string is recovered from storage, and B is the connection of a neuron with a block of neurons. The second rule .→(f...f)n, means replace the start point by the neurons of the input layer. Rule 3.1 (f→[f) means to store the position of the current neuron, so as to start a new ramification from it. Rule 3.2 (f→fFf) means establish a connection between two neurons. Rule 3.3 (f→fF) means establishing a connection from a specific neuron. Rule 3.4 (f→n) means replace a provisional neuron with a permanent neuron. Rule 3.5 (f→f) means to maintain a specific neuron during development. Rule 3.6 (f→fB) means connect a neuron to a block of neurons. Rule 4 ([→[Ff]) means start the development of a new ramification from a specific neuron and recover the previous state. Rule 5(f→f*) means recover a previous ramification stored for use.

As a simple example, suppose that starting with the axiom (α = .) twice , and applying the second production rule $. \rightarrow f$ to the axiom twice, the resulting string is **ff**. Applying the third rule (3.1) $f \rightarrow [f$ to string **ff** yields a new string, **[f[f]**. After one, two, three and applications of the fourth rule $[\rightarrow [Ff]$ on string **[f[f**, the string becomes **[Ff]Ff]f[Ff]Ff]f**. Applying the rule (3.3) $f \rightarrow$**fFf** eight time to the previous string, the resulting string is **[FfFfFf]FfFfFf]f [FfFfFf]FfFfFf]f** . After Applying the (3.6) $f \rightarrow$**fB** to the previous string the resulting string is **[FfBFfBFfB]FfBFfBFfB]f [FfBFfBFfB]FfBFfBFfB]f**. Finally applying the rule (3.4) $f \rightarrow$**n** to the previous string the resulting string is **[FfnFfnFfn]FfnFfnFfn]f [FfBFfBFfB]FfBFfBFfB]f**. This phenotype represents the RNA structure shown in Fig. 2.

B. Rule extraction by genetic algorithms

The neurons generated in the previous subsection are developed after the following process. To formulate a biologically realistic GA, we let the genes of the chromosomes (sequences of hypothetical DNA) encode a recipe (the production rules of the L-system described in subsection V.A and illustrated in Table I). The recursive rules in Table I drive the developmental stages of the neurons (Fig. 2).

	00 (U)	01 (C)	10 (G)	11 (A)	
00 (U)	f (UUU)	F (UCU)	n (UAU)	. (UGU)	00 (U)
00 (U)	n (UUC)	. (UCC)	f (UAC)	F (UGC)	01 (C)
00 (U)	F (UUA)	f (UCA)	B (UAA)	f (UGA)	10 (A)
00 (U)	[(UUG)	n (UCG)	[(UAG)	* (UGG)	11 (G)
01 (C)	f (CUU)	] (CCU)	n (CAU)	* (CGU)	00 (U)
01 (C)	* (CUC)	F (CCC)	f (CAC)	F (CGC)	01 (C)
01 (C)	] (CUA)	f (CCA)	* (CAA)	[(CGA)	10 (A)
01 (C)	f (CUG)	* (CCG)	B (CAG)	] (CGG)	11 (G)
10 (A)	* (AUU)	] (ACU)	n (AAU)	f (AGU)	00 (U)
10 (A)	f (AUC))	B (ACC)	f (AAC)	B (AGC)	01 (C)
10 (A)	F (AUA)	[(ACA)	B (AAA)	n (AGA)	10 (A)
10 (A)	* (AUG)	f (ACG)	* (AAG)	] (AGG)	11 (G)
11 (G)	] (GUU)	[(GCU)	F (GAU)	n (GGU)	00 (U)
11 (G)	n (GUC)	B (GCC)	[(GAC)	. (GGC)	01 (C)
11 (G)	f (GUA)	] (CGA)	B (GAA)	F (GGA)	10 (A)
11 (G)	B (GUG)	f (GCG)	* (GAG)	[(GGG)	11 (G)

TABLE II
THE GENETIC CODE FROM THE PERSPECTIVE OF MRNA, TRANSLATED AS IN FIG. 3(B). IN THE SAME TABLE, THE DNA'S METAPHOR

In biological genetic processing Fig. 3(b), DNA is transcribed into ribonucleic acid (RNA), and the RNA is translated into proteins. The proteins are derived from linear sequences of amino acids encoded by codons (groups of three nucleotides selected among U, G, A, and G of the genetic code (Table II). In Fig. 3(b), the protein is formed by a sequence of amino acids starting with methionine (Met) and ending with proline (Pro). Such protein synthesis triggers all stages of the neuronal development (phenotypic effects), as shown in Fig. 3(b). The elements of the alphabet $\Sigma = \{., f, F, n, [,], *, B, \}$ of the L-system, described in subsection V.A and displayed in bold font in Table II, are a metaphor of the genetic code. Each two-bit sequence represents one nucleotide; for example, the set (00, 01, 10, 11) symbolizes (U, C, A, G) in the original genetic code. Accordingly, six bits represent three nucleotides; that is, (000000, 011111) symbolizes (UUU, CGG). In the algorithm (Function-Rule-Extraction-with-GA) shown in the next page, the funtion COMPLEMENT(B,S,I,G) mimic the DNA transcription process into RNA, as shown in Fig. 3(b).

All integer strings obrained after te execution of CONSTRUCT-S(B,S,I,G) are stored in the array "S". The function FIND-SUBSTRING(S,I,G) translates the integer string to valid production rules of the L-System (Table I). The function FIND-SUBSTRING(S,I,G), also mimics the translation process of RNA into protein. Fig.3(a) illustrates, an example of rule extraction for a single individual of the population. In this figure, the transcription string yields the integer string B.f[Ff.nB]Bf. We seek the shortest string containing all valid rules; in this case, **.f[Ff *nB]**.

C. Neural Network

Neural Networks have beeen successfully aplied to a variety of complex problmes due to its ability to learn non-linear relationships between input and output patterns, which would be difficult to model conventional methods [3]. In this research, ADEANN-Deep enables automatic design of different

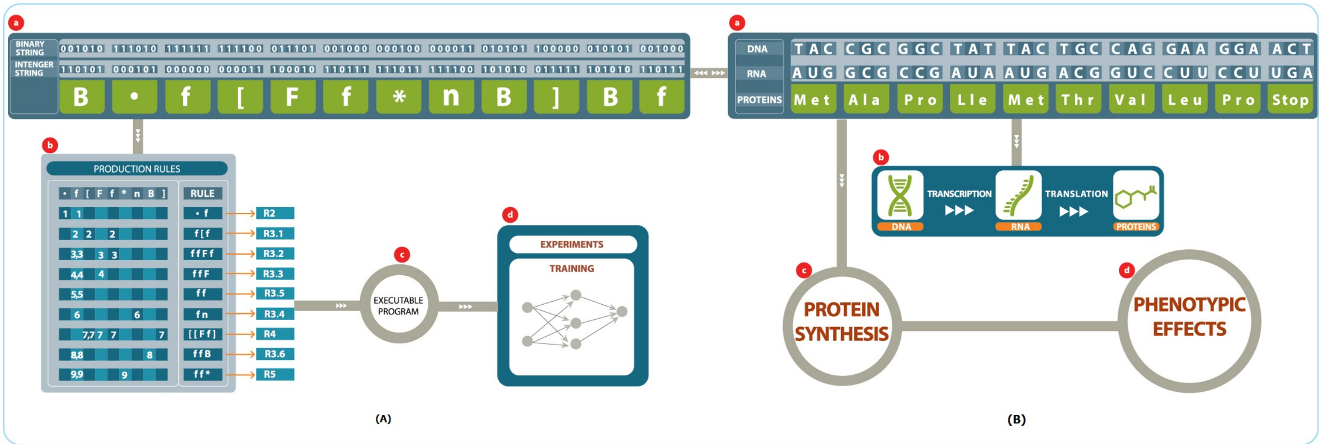

Fig. 3. (b) DNA transcription into RNA and translation of RNA into protein. (a) In the analogous artificial process, a binary string is transcribed into an integer string and the string is translated into the production rules of the L-system.

recurrent and deep neural network architectures that yields the best generalization accuracy for each submarket.

VI. Material and Methods

A. Explanatory Variable Selection in Prediction Models

In prediction models, the explanatory variable can explain or cause differences in a response variable. After the identification of the explanatory variables, an explanatory variable selection method is applied to find the optimal set of input variables required to describe the behavior of the energy price, which should contain a minimum degree of redundancy. The aim is to test how two or more variables act togheter to affect the output variable and determine whether they improve the prediction of the desired value. The PLDs prediction has rhe following referenced variables: stored energy in reservoirs (%MLT), inflow energy in reservoirs (%MLT), total hydro generation (MWmed), total thermal generation (MWmed), system power load (MWmed). Below, we detail the variables chosen in the work of [3] for each submarket, : North:Stored energy, Inflow energy and Load, Northeast:Stored energy, Inflow energy , Thermal generation and Load. Center-Wets/Southeast:Stored energy, Hydro generation, Thermal generation and Load, South:Stored Enregy, Hydro generation, Thermal generation and load. We applied the same type of selection used in the each submarket variables.

B. Dataset Description

The dataset used in this research contains the electricity prices data taken from Brazilian Electrical Energy Commercialization Chamber website [5] presented on a weekly basis, in addition to the explanatory variables data taken from Brazilain National System Operator website [6]. In the simulations we applied the dataset constructed by [3] (period from 2002 to 2009) to each submarket:North, Northeast, South and Center-West/Southeast.

C. Used Metrics

The hybrid system proposed in this system is applied to the Brazilian electricity market. Some metrics commonly used to evaluate proce forecasting accuracy are employed in this paper ; root mean squared error (RMSE) , mean absolute error (MAE) . These quantities are calculate by:

$$MAE = \frac{1}{N}\Sigma_{i=1}^{N}|p_i true - p_i forecast| \quad (1)$$

$$RMSE = \sqrt{\frac{1}{N}\Sigma_{i=1}^{N}\left(p_i true - p_i forecast\right)^2} \quad (2)$$

$$MAPE = \frac{1}{N}\Sigma_{i=1}^{N}\frac{|p_i true - p_i forecast|}{\frac{1}{N}\Sigma_{i=1}^{N}p_i true}x100\% \quad (3)$$

Where N is the number of samples, $p_i true$ is the actual price and $p_i forecast$ is the forecasted price.

D. Statistics

We repeated each experiment five times. The independence of the events was assured since the runs were independent and had randomly generated initial seeds. Furthermore, to evaluate the significance of the results obtained from ADEANN and the other NEAs, we carried out t-tests with a confidence level of 95% (i.e., a p-value under 0.05). To statistically compare the performances of two NEAs for the classification problems, we considered the three following criteria: RMSE as the primary criterion, MAPE as the second one, and MAE as the third one. Similarly to [13], without the occurrence of any significant statistical differences between the RMSE, MAPE, and MAE values of two NEAs on a given dataset, it was considered that both algorithms performed equally well. In this case, both algorithms receive 1 point. In contrast, if two algorithms obtain significantly different RMSE or MAPE or MAE scores, the better performing algorithm receive two points and the other zero points. Consequently, H_0 and accept the alternative hypothesis H_1. In deciding whether two performances differ, we test the significance of the difference between u_1 and u_2 ($p < 0.05$). The overall performance of each NEA is then calculated by summing all points achieved in the pairwise comparisons.

Function-Rule-Extraction-with-GA

```
Inputs:
B:=[IxG] //I is the number of individuals in the population
S:=[IxG] //G is the number of desired genes
COMPLEMENT(B,S,I,G);
for k:=0 to I-1
    CONSTRUCT-S(B,S,I,G);
for k:=0 to I-1
    FIND-SUBSTRING(B,S,I,G);

void CONSTRUCT-S(B,S,I,G);
  vars: start←0;end←5;cont←0;String s←"";
    while (start <= (G-1))
        for (j:=start; j<= end; j++)
            s←s+(char)B[k,j];
        S[k,cont]←TABLE-CONVERT(s);
        s←" ";cont←cont+1;
        start←start+6;
        end←end+6;

int FIND-SUBSTRING(B,S,I,G);
vars:
char main-string[G/6], sub-string[G/6];
int find-char, exist, num-chars, i, j;
sub-string[]←".f[Ff*nB]";
for (j:=0; j< ((G/6)-1); j++)
    main-string[j]←S[i,j];
    num-chars←strlen(sub-string);
    while(main-string[i]! = end − of − string)
        if (main-string[i]==sub-string[j])
          i++;j++;find-char←1;
          if (j==num-chars)
            j←0;exist←1;
        else
          if (find-char==1)
            j←0;find-char←0;
          else i++
    if(exist) return 1;
     else return 0
end.
```

E. Data Preparation

Many problems are involved in the analysis of rare patterns of ocurrences. As an example, Figure 7 shows the histogram of the PLD series for the North region. It shows that some patterns occur more often than others. In addition, most of the time the price remains at low values, under R$100.00 and the energy price rarely reaches values above R$300.00. However, neural networks are sensitive to imbalanced data sets since it causes difficulties in the learning process and can deteriorate the model performance. Then the data balancing was applied in this paper during data preparation process. Figures 8 shows the histogram of the PLD series, before and after data balancing, for the North region.

Variable	Minimun	Mean	Maximum	Std.Deviation
Stored energy	20.71	65.30	87.64	16.7
Inflow energy	47.86	103.87	182.00	24.38
Hydro generation	8854.14	17.635.02	23.378.14	3253.84
Thermal generation	192.86	1112.57	3258.86	615.93
Load	19.295.57	28.048.88	34.668.00	3148.61
PLD	4.0	74.65	684.00	117.53

TABLE III
SUMMARY STATISTICS OF THE VARIABLES FROM CENTER-WEST/SOUTHEAST REGION. FONT: [3]

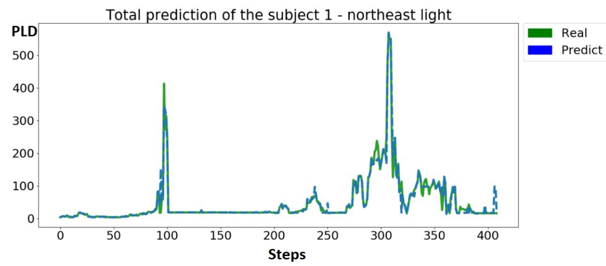

Fig. 4. Energy price observed and predicted with the hybrid model to Northeast Region (Light PLD) - UnBalanced Data

VII. SIMULATION RESULTS

The methodology proposed in this paper is applied to the Brazilian electricity market and some criteria commonly used to evaluate price forecasting accuracy are employed, such as RMSE, MAE and MAPE.

A. Unbalanced Data

Tables VI and VII illustrate the values of RMSE, MAE, and MAPE obtained from ADEANN-Deep for the Northeast and

	RMSE	MAE	MAPE
Medim PLD	11.40	8.05	0.21
light PLD	11.07	7.82	0.20
heavy PLD	11.59	8.20	0.21
Average	11.35	8.02	0.21

TABLE IV
ENERGY PRICE ERROR MEASURES OBTAINED WITH THE PROPOSED HYBRID SYSTEM 36-WEEKS AHEAD - SOUTH REGION (UNBALANCED DATA)

	RMSE	MAE	MAPE
Medim PLD	9.35	6.61	0.22
light PLD	9.27	6.55	0.20
heavy PLD	10.48	7.41	0.22
Average	9.70	6.86	0.22

TABLE V
ENERGY PRICE ERROR MEASURES OBTAINED WITH THE PROPOSED HYBRID SYSTEM 36-WEEKS AHEAD - NORTH REGION (UNBALANCED DATA)

	RMSE	MAE	MAPE
Medim PLD	9.03	6.38	0.19
light PLD	10.21	7.22	0.21
heavy PLD	9.01	6.37	0.18
Average	9.412	6.66	0.19

TABLE VI
ENERGY PRICE ERROR MEASURES OBTAINED WITH THE PROPOSED HYBRID SYSTEM 36-WEEKS AHEAD - NORTHEAST REGION - (UNBALANCED DATA)

	RMSE	MAE	MAPE
Medim PLD	15.47	10.948	0.20
light PLD	15.47	10.94	0.20
heavy PLD	17.15	12.13	0.22
Average	16.122	7.69	0.20

TABLE VII
ENERGY PRICE ERROR MEASURES OBTAINED WITH THE PROPOSED HYBRID SYSTEM 36-WEEKS AHEAD - SOUTHEAST REGION - (UNBALANCED DATA)

Southeast regions. Figures 4 and 5 show the short-term price observed and predicted with the proposed hybrid system 36-weeks ahead. For the Southeast region, the RMSE and MAE obtained from ADEANN-Deep 16.12 R$/Mwh and 7.69 R$/ Mwh were higher than those obtained from the Hybrid System 9 R$/Mwh and 3 R$/Mwh [3]. However, the value of MAPE 0.20 R$/Mwh reached using ADEANN-Deep was below that obtained from the Hybrid System [3], which generated a MAPE value equal to 5 R$/ Mwh. For the Northeast region, the RMSE and MAE achieved using ADEANN-Deep 9.41 R$/Mwh and 6.66 R$/ Mwh were higher than those from the Hybrid System 9 R$/Mwh and 3 R$/Mwh [3]. However, the value of MAPE 0.19 R$/Mwh generated from ADEANN-Deep was below that from the Hybrid System [3], which reached a MAPE value equal to 4.5 R$/ Mwh. Tables IV and V describe the average values of RMSE, MAE and MAPE values obtained from ADEANN-Deep for the North and South Regions, respectively. Figure 6 shows the short-term price observed and predicted with the proposed hybrid system 36-weeks ahead to North region. For the South region, the RMSE and MAE generated from ADEANN-Deep 11.35 R$/Mwh and 8.02 R$/ Mwh were above those from the Hybrid System 9 R$/Mwh and 3 R$/Mwh [3]. However, the value of MAPE 0.21 R$/Mwh reached using ADEANN-Deep was lower than that achieved using the Hybrid System [3], which generated a MAPE value equal to 5 R$/ Mwh. For the North region, the RMSE and MAE obtained from ADEANN-Deep 9.70 R$/Mwh and 6.86 R$/ Mwh were higher than those from the Hybrid System 7.5 R$/Mwh and 2.5 R$/Mwh [3]. However, the value of MAPE 0.20 R$/Mwh generated using ADEANN-Deep was below that obtained from the Hybrid System [3], which reached a MAPE value equal to 4.8 R$/ Mwh.

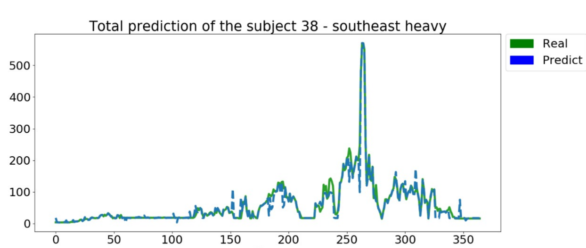

Fig. 5. Energy price observed and predicted with the hybrid model to Southeast Region (heavy PLD) - UnBalanced Data

B. Balanced Data

The analysis of the results for the South region revealed a mean square error (RMSE) generated using ADEANN-Deep of 8.20 R$ Mwh, lower than 9 R$/Mwh, obtained from the Hybrid model [3]. The MAE and MAPE generated using ADEANN-Deep were 5.80 R$/ Mwh and 0.19 R$/Mwh, respectively, while the values obtained from the hybrid method [3] were 3 R$/ Mwh and 5 R$/ Mwh, respectively. Therefore, our MAE value was higher than that obtained from the hybrid system, while our MAPE value was below it. For the North region, the mean square error (RMSE) generated from ADEANN-Deep was 5.02 R$/Mwh, lower than 7.5 R$/Mwh, reached using the hybrid [3]. The MAE and MAPE obtained using ADEANN-Deep were 3.55 R$/ Mwh and 0.12 R$/ Mwh, respectively, while the values generated using the hybrid model [3] were 2.5 R$/Mwh and 4.8 R$/Mwh, respectively. Therefore, our MAE value was higher than that from the hybrid system and our MAPE value was below it. Tables VIII and IX describe the values obtained and the average values of RMSE, MAE and MAPE values generated from ADEANN-Deep.

The analysis of the results for the Southeast region revealed a mean square error (RMSE) using the ADEANN-Deep of 9.8 R$ Mwh, higher than 9.4 R$/Mwh, obtained from the Hybrid model [3]. The MAE and MAPE reached using ADEANN-Deep were 6.93 R$/ Mwh and 0.14 R$/Mwh, respectively, while the values from the hybrid method [3] were 5 R$/ Mwh and 4 R$/ Mwh, respectively. Therefore, our MAE value was higher than that obtained from the hybrid system and our MAPE value was below it. For the Northeast region, the mean square error (RMSE) generated from ADEANN-Deep was 5.1 R$/Mwh, lower than 8 R$/Mwh, obtained from the hybrid model [3]. The MAE and MAPE generated using ADEANN-Deep were 4.1 R$/ Mwh and 0.16 R$/ Mwh, respectively, while the values obtained from the hybrid model [3] were 4 R$/Mwh and 5 R$/Mwh, respectively. Therefore, our MAE value was higher than that reached using the hybrid system and our MAPE value was below it. It is noteworthy that all other models are forecasting 12 weeks ahead, however, ADEANN-Deep is forecasting 36 weeks ahead.

VIII. CONCLUSIONS

In this paper a hybrid approach is proposed for a short-term energy price prediction. The model considers multi-step ahead price prediction (36 weeks-ahed) and is applied to the Brazilian electricity market. The results obtained are compared with the study of [3] and others methods in section VII. The results obtained from ADEANN-Deep applied to

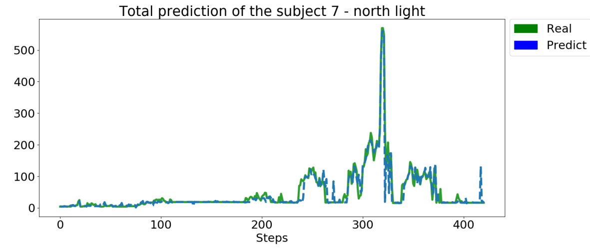

Fig. 6. Energy price observed and predicted with ADEANN-DEPP for the North region (Light PLD) - Unbalanced Data.

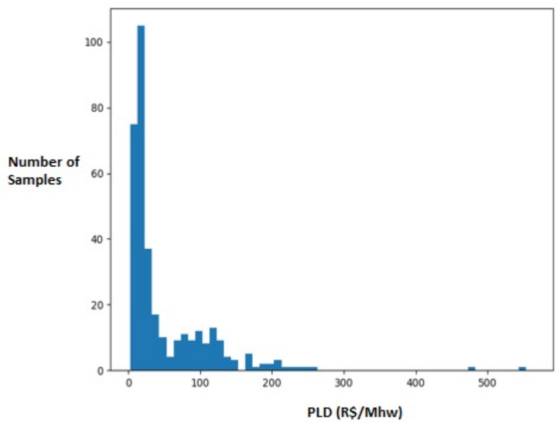

Fig. 7. Histrogram of the PLD series to North Region.

the Brazilian market presented a sufficiently good accuracy level compared to other methods described in section VII. Data balancing and the use of explanatory variables were essential for having improved the results generated using ADEANN-Deep, according to the results presented in section VII.B. Statistical test (textitt-test) with confidence level of 95% shows that in 58.33% of the cases ADEANN-Deep provides better results than the hybrid system [3]. In addition, the new version of the hybrid system (ADEANN-Deep), using Keras, enhances the possibilities of using multiple deep recurring

	RMSE	MAE	MAPE
Medim PLD	7.52	5.31	0.18
light PLD	8.52	6.02	0.20
heavy PLD	8.57	6.06	0.19
Average	8.20	5.80	0.19

TABLE VIII
ENERGY PRICE ERROR MEASURES OBTAINDE WITH THE PROPOSED HYBRID SYSTEM 36-WEEKS AHEAD - SOUTH REGION - BALANCED DATA

	RMSE	MAE	MAPE
Medim PLD	4.22	2.98	0.11
light PLD	5.20	3.68	0.13
heavy PLD	5.64	3.99	0.14
Average	5.02	3.55	0.12

TABLE IX
ENERGY PRICE ERROR MEASURES OBTAINED WITH THE PROPOSED HYBRID SYSTEM 36-WEEKS AHEAD - NORTH REGION - BALANCED DATA

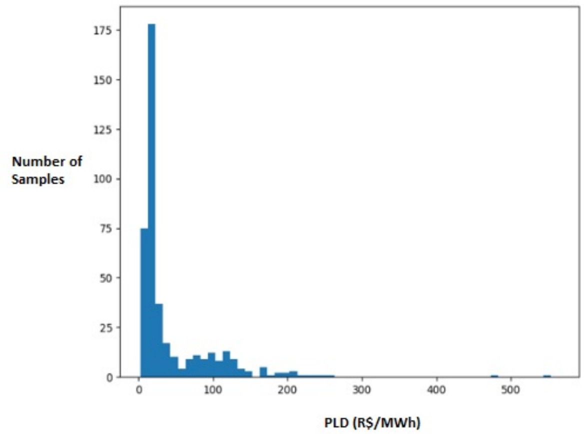

Fig. 8. Histrogram of the PLD series to North Region (after data balancing).

Neural Network architectures.

ACKNOWLEDGMENT

We would like to thank the Federal University of Pará who supported this study.

REFERENCES

[1] D.E. Kazaryan, A.V. Savinkov, Grammatical Evolution for Neural Network Optimization in the Control System Synthesis Problem, Procedia Computer Science, Volume 103, 2017.
[2] Patel, O.P., Tiwari, A. Bagade, V. Quantum-Inspired Stacked Auto-encoder-Based Deep Neural Network Algorithm (Q-DNN). Arab J Sci Eng (2018) 43: 6929. https://doi.org/10.1007/s13369-017-2907-2
[3] Jose C. Reston Filho, Carolina de M. Affonso, Roberto C.L. de Oliveira, Energy price prediction multi-step ahead using hybrid model in the Brazilian market, Electric Power Systems Research, Volume 117, 2014, Pages 115-122.
[4] Mohsen Hayati , 2007. Short Term Load Forecasting Using Artificial Neural Networks for the West of Iran. Journal of Applied Sciences, 7: 1582-1588.
[5] Website of Brazilian Electrical Energy Commercialization Chamber . http://www.ccee.org.br/
[6] Website of Brazilain National System Operator http://www.ons.org.br/home/
[7] De Campos, L.M.L, De Oliveira, R.C.L, De Campos, G.A.L.A NEUROGENETIC ALGORITHM BASED ON RATIONAL AGENTS.COMPUTING AND INFORMATICS, VOL 37, NO 5 (2018).
[8] Oluwarotimi W.S., Grace M.A., Arun K.S., Guanglin L., Computational Intelligence Enabling the Development of Efficient Clinical Decision Support Systems: Case Study of Heart Failure.In Intelligent Data-Centric Systems, Computational Intelligence for Multimedia Big Data on the Cloud with Engineering Applications, Academic Press, 2018.
[9] A. J. Conejo, M. A. Plazas, R. Espinola and A. B. Molina, "Day-ahead electricity price forecasting using the wavelet transform and ARIMA models," in IEEE Transactions on Power Systems, vol. 20, no. 2, pp. 1035-1042, May 2005.
[10] Deepak Singhal, K.S. Swarup,Electricity price forecasting using artificial neural networks, International Journal of Electrical Power and Energy Systems, Volume 33, Issue 3, 2011,Pages 550-555.
[11] De Campos,L.M.L,de Oliveira,R.C.l., Roisenberg, M., Optimization of neural networks through grammatical evolution and a genetic algorithm, Expert Systems with Applications, Volume 56, 2016,Pages 368-384.
[12] RUSSEL, S.; NORVIG, P.; Artificial Inteligence: A Modern Approach. Prentice-Hall, Second Edition, 2013.
[13] M. Castellani 2013, "Evolutionary generation of neural network classifiers—An empirical comparison," Neurocomput. 99, 214–229.