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CONSUMPTION FORECASTING AND ECONOMIC-FINANCIAL EVALUATION OF A BRAZILIAN COMPANY IN THE FREE MARKET

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Resumo – A diferença essencial entre o Ambiente de Contratação Livre (ACL) e o Ambiente de Contratação Regulada (ACR) é a possibilidade de negociar livremente prazos e preços de energia com fornecedores. Desvinculados das tarifas reguladas pelo governo, no ACL, os consumidores arcam com a onerosa diferença entre a energia contratada e a consumida. Esse custo pode ser reduzido com o conhecimento preciso do perfil do consumidor, a partir da análise de dados históricos. Neste artigo, é proposta uma metodologia que permite avaliar a migração de consumidores para o ACL. Em um estudo de caso, técnicas estatísticas gráficas ajudam a identificar o perfil de um consumidor da cidade do Rio de Janeiro, subgrupo A4 e com modalidade tarifária verde, no período de 2016 a 2019. Em seguida, métodos clássicos e baseados em redes neurais artificiais são utilizados para a previsão de consumo doze meses à frente. Em particular, as redes de Memórias de Longo e de Curto Prazos (LSTM) tiveram um desempenho melhor do que modelos Autorregressivos Integrados de Médias Móveis (ARIMA). Ao final, é demonstrado com indicadores econômicos e financeiros, a decisão acertada desse consumidor em migrar para o ACL, anteriormente à análise realizada neste estudo de caso.

Palavras-chave – Mercado livre de energia, previsão de séries temporais, redes neurais artificiais, LSTM.

Abstract – The essential difference between the Free Contracting Environment (FCE) and the Regulated Contracting Environment (RCE) is the possibility of freely negotiating energy terms and prices with suppliers. Disconnected from the tariffs regulated by the government, in the FCE, consumers bear the costly difference between the contracted energy and that consumed. This cost can be reduced with accurate knowledge of the consumer profile, based on the analysis of historical data. In this article, a methodology is proposed to evaluate the migration of consumers to the FCE. In a case study, graphical statistical techniques help identify the profile of a consumer in the city of Rio de Janeiro, subgroup A4 and with green tariff modality, in the period from 2016 to 2019. Then, classical and artificial neural network-based methods are used for consumption forecasting twelve months ahead. In particular, Long and Short Term Memories (LSTM) networks performed better than Autoregressive Integrated Moving Average (ARIMA) models. At the end, it is demonstrated with economic and financial indicators, the right decision of this consumer to migrate to the FCE, prior to the analysis performed in this case study.

Keywords – Free energy market, time series forecasting, artificial neural networks, LSTM.

1. INTRODUCTION

The Energy Research Company (EPE, in Portuguese) estimates that the installed capacity for electricity generation will increase 37% in the next ten years, reaching 275 GW in 2031, with wind and solar sources gaining space in the Brazilian matrix, while hydro will have its share reduced to less than 50% [1]. In this same horizon, an average growth of 2.9% per year of the Brazilian GDP is forecast. These reinforce the prominent position of the Brazilian electricity market globally.

The expansion of the electrical sector in Brazil, motivated by economic development and by the offer of new renewable energy sources, was fundamental for the creation of the free energy contracting model. The standard for commercialization of state-owned energy showed itself to be unsustainable and inefficient in the face of new economic and social demands, highlighting the need for the implementation of a competitive market, with increased efficiency of the energy companies, as well as allowing a clearer budget forecast with savings for the consumer [2].

According to the Brazilian Association of Energy Sellers (ABRACEEL, in Portuguese) [3], in July 2020, about 80% of Brazil's industrial energy consumption was already part of the free market. This represented 32% of all electricity consumption in the country, and with a tendency to increase. Data released recently by the Chamber of Commercialization of Electrical Energy (CCEE) [4] show that, despite the restrictions imposed in large capital cities as a measure to contain the advance of COVID-19, the volumes consumed in the first month of the year followed the trend of the end of 2020. The Regulated Contracting Environment (RCE) fell by 0.5%, while the Free Contracting Environment (FCE) increased by 10.7%. This has been consolidated as a solution for both consumers and generators.

After the observation of strong impacts from the COVID-19 pandemic throughout 2020 and 2021, final energy consumption is expected to grow again closer to normality. The EPE estimates a growth in final energy consumption of 1.9% per year until 2031, reaching 333 TOEs[1].

In the FCE, the consumer is the one who defines the contracting strategy and decides how to purchase electricity. The greatest risk is the volatility of the price of electrical energy, especially during periods of drought. Besides making quotations with several energy suppliers and also closing short or long term negotiations with defined prices and readjustments, the consumer needs to assess his consumption profile and evaluate the financial parameters to perform the migration with less risk.

The contribution of this paper is in defining a methodology that can assist final consumers in identifying their electricity usage profile. With this information, one can accurately predict energy consumption so that the best contractual conditions can be negotiated with the energy suppliers, minimizing the need to purchase at different contract values.

In order to establish the amount of energy and the contract period, tools must be used to estimate consumption with the lowest percentage of error, aiming to reduce expenses with electricity resulting from the wrong choice of the best alternative in the purchase of energy. Thus, in this work, forecasts of the consumption series of a consumer of subgroup A4 and green tariff mode, in the concession area of Light, which operates in the state of Rio de Janeiro, were performed in the period from 2016 to 2019, with long and short-term memory neural networks (LSTM) and with the autoregressive integrated and moving average statistical model (ARIMA). Next, the expenses that the consumer would have in the RCE were simulated. And finally, the financial evaluation of the migration project to the FCE, if the consumer were still in the RCE.

The remainder of this paper is divided into seven more sections. The second section outlines the related work on systems with research studies to forecast electricity consumption. The third section presents the Brazilian Electrical Energy Market, from the standpoint of the types of consumers. The fourth section details the Free Energy Market. The fifth section briefly reviews the fundamentals of time series forecasting and economic evaluation. The sixty section presents the methodology used in this work to perform the evaluation for migration from RCE to FCE. The seventh section describes the Case Study and, finally, the last section discusses the results obtained and presents perspectives for further work.

2. RELATED WORKS

According to the international electric power freedom ranking (ABRACEEL), more than fifty countries have already reorganized their electrical systems, shifting from a vertically integrated structure of state companies to a structure of separate businesses (unbundling) [5]. With this deregulation of the electricity markets, competition was introduced for the generation and retail businesses. The generators comprise the market supply, while the retailers aggregate energy demands, which they then deliver to end users. In such environments, electricity can be traded freely, like any commodity, so the price of electricity can reflect the relationship between supply and demand. Thus, forecasting the price of energy is essential to the functioning of this market.

In the last few years, a significant number of papers have addressed the Electricity Price Forecast (EPF) with a variety of methods and models to capture the complex dynamics and achieve further improvements in electricity spot price forecasts. This is because electricity demand depends on many factors, such as weather, economic growth, and fuel prices, that cause the price to fluctuate frequently. Thus, performing EPF accurately is a major computational challenge.

The importance of the electricity price for both producers and resellers who perform day-ahead forecasting [6] for defining profit maximization strategies at bids is indisputable. At the end of this chain, the final consumer seeks alternatives to reduce electricity expenses.

Basically, time series forecasting methods fall into three categories: statistical models, models based on artificial intelligence, and hybrid models. Statistical models, usually linear, work well for problems with small amounts of data. Autoregressive Integrated Moving Average (ARIMA) [7] is one of the most widely used methods for time series forecasting. On the other hand, artificial neural networks, fuzzy systems, support vector machines, and evolutionary computation are Computational Intelligence models [8] that have flexibility and the capacity to handle complex and non-linear data.

With less complex relationships between variables than the EPF task, load forecasting has become of great importance for final consumers eligible to migrate to the free market that have in this energy contracting environment an effective opportunity to reduce expenses with electricity. However, according to the research of [9], companies do not know how to accurately assess the optimal amount of electricity to be purchased in the short and long term markets. This results in contracts being drawn up with forecasts of up to 40% fluctuation in electricity consumption in the long term. Even when paying higher than average prices, this condition adds value to the buyer because these companies are typically economic sectors (industries) that are unstable or strongly affected by seasonality.

[1] Tons of Oil Equivalent

The same techniques used in EPF have been proposed to support economic feasibility analysis, although the literature presents few studies on the migration of consumers to the free market.

3. BRAZILIAN ELECTRICAL ENERGY MARKET

The electricity sector is composed of several segments that are organized from generation to distribution. At the end of this production chain are the consumers who, in turn, are classified into groups related to the load and the energy supplier [10].

The following will briefly describe the existing power contracting environments and models.

3.1 Environments and electrical energy contracting models

In the RCE or captive market, consumers are restricted to buying energy from companies that hold the concession right. Therefore, their purchase is linked to mandatory contracting with the distributor in the region where they are located. The tariffs for energy consumption are fixed by the National Electric Energy Agency (ANEEL in the Portuguese acronym) and cannot be negotiated. In the RCE are all residential consumers, as well as some commercial, industrial, and rural consumers [11].

On the other hand, the FCE or free market is characterized as an environment in which consumers can choose to purchase energy from various generating sources, exercising the right to portability and the effective reduction in the cost of energy. In this environment, there are two types of consumers: free and special. The latter have the option to negotiate with suppliers and the conditions of energy contracting [11].

3.2 Captive Consumers

These are consumers that belong to the RCE. They do not have the freedom to choose their supplier, and are therefore subject to the payment of the tariff determined by ANEEL. They are also susceptible to the variations of the tariff flags. In this case, consumers are served by the energy distributor in the region where they are located [11].

3.3 Free Consumers

They have at least 1,000 kW of contracted demand and can buy energy from incentivized or conventional sources, from any generation source, connected to any voltage. It should also be noted that this limit will be reduced to 500 KW as of January 2023 [12].

3.4 Special Consumers

They have contracted demand equal to or greater than 500 kW and less than 1,500 kW, regardless of voltage level. They can contract energy only from wind, solar, biomass, small hydroelectric plants or hydraulic plants of companies with power equal to or less than 30,000 kW, the so-called special sources of energy or sources of stimulated energy. The contracting of this type of energy is linked to a discount of 50% to 100% in the value of the Distribution System Utilization Tariff (TUSD, in Portuguese). This is an incentive that the government makes available for the expansion of these generating sources in the National Interconnected System (SIN, in Portuguese) [12].

4. FREE ENERGY MARKET

Having established the characteristics of the free energy market, it is necessary to highlight the advantages, risks, and the process of joining this type of contracting modality.

4.1 Benefits of the free energy market

Some advantages in migrating to the FCE include:

- Reduction in the cost of energy;
- Cost predictability;
- Tariff flags are not applicable to free consumers;
- Purchase of energy from sustainable sources;
- Fixed price for peak and off-peak hours.

4.2 Risks associated with the FCE

One of the biggest risks in the FCE is the non-management of short and long term prices: inadequate planning, when contracting the amount of energy, may result in the consumer being exposed to the weekly Difference Settlement Price (DSP), used in energy buying and selling operations in the short term market, also known as the *spot* market. This price is based on the Marginal Operation Cost (MOC) and is mainly influenced by the climatic conditions (rainfall) and the load increase in the system [13].

The DSP is stipulated every week by the CCEE, limited by a maximum and minimum amount. It defines the value of 1 MWh additionally produced and expected for the following week of operation. Its value is divided by load level and submarket and equals the generation cost of the next thermal plant that will dispatch energy at the time. Thermoelectric plants depend on fuels and their prices are higher than those of hydroelectric plants, thus directly affecting the cost of electricity generation in the country.

It can be seen in Fig. 1 that the DSP follows the MOC profile for average values, except for the months when the MOC exceeds the DSP. When this occurs, the difference is converted into charges [14]. From the end consumer's perspective, a contract based on the methodology proposed in this paper, with an adequate profile survey and accurate consumption forecast, plus good consumption management, will protect them from DSP variations.

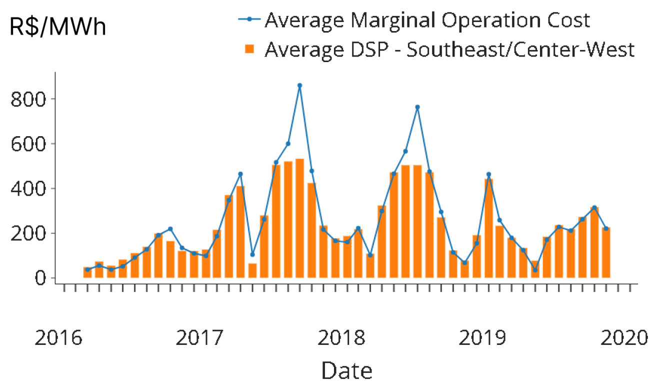

Figure 1: Average MOC and DSP in the Southeast/Center-West submarkets.

4.3 Free market adhesion process

The evaluation of the voltage and demand requirements is a primary factor for adhesion to the FCE. The consumer must have a minimum contracted demand of 500 kW to become a special consumer.

There is also the possibility of migration by communion, in which all the units of a given consumer, with the same National Register of Legal Entities (CNPJ, in Portuguese), in the same concession area of the energy distributor or located in contiguous areas (without separation by public roads), may aggregate loads to reach the minimum demand level required to become a special consumer, such as, for example, a network of stores with demand levels lower than 500 kW, but which, when added together, reach the required level. On the other hand, the requirement to become a free consumer is 2 MW of demand per unit. In this category there is no possibility of migration by communion [11].

The analysis of the current contracts with the distributor should be reviewed, because they are valid for 12 months on the energy supply. These must be terminated 6 months in advance of the migration. After the analysis of the contracts in effect, the consumer should compare the forecasts of electricity expenses in the free contracting environment and in the regulated environment, making a comparison of these data.

Next, if the consumer decides to migrate to the FCE, he must send a letter to the distributor, informing about the termination of the current contracts. If the current contract is terminated early, the consumer must pay for its termination.

The next step consists in acquiring energy in the FCE, through Energy Commercialization Contracts in the Free Contracting Environment (ECCFE) and/or Incentivized Energy Commercialization Contracts (IECC). The contract can be signed by commercializing agents, generators or other consumers [11].

Subsequently, the Measurement and Billing System (MBS) is adapted. At this stage of the migration process it is essential that consumers perform the adequacy according to the network procedure [11].

Last but not least important, it is necessary to adhere to the Chamber of Commercialization of Electrical Energy (CCEE) and perform the modeling of the energy contracts acquired in the FCE, according to CCEE's commercialization procedures. As of the adhesion, the monthly payment of the associative contribution to the CCEE becomes compulsory, referring to the operational costs that are prorated among the agents according to the volume of energy negotiated by each one.

5 Theoretical Background

This section presents the evaluation of the energy consumption forecasts and the description of the techniques considered to measure the savings that the free trading model provides. The traditional evaluation metrics that will allow comparing such forecasting models based on artificial neural networks with the autoregressive integrated moving average model (ARIMA) are presented.

5.1 Time series forecasting

Since energy consumption is variable, it is necessary to perform studies related to the historical behavior of the consumer at different times. The fundamental part of this analysis is to determine the amount of energy to be contracted, linked to a certain effective purchase period. Different approaches can be employed for forecasting [15–17], including the ARIMA model [18] and artificial neural networks [19, 20].

5.2 ARIMA Model

The Box-Jenkins methodology, also known as Autoregressive Integrated Moving Average - ARIMA (p, d, q) is a classic statistical model for time series forecasting.

It consists of fitting integrated moving average autoregressive models, where p is related to the AR term (autoregressive parameter), the d parameter relates to the I term (integrated parameter) and q, to the MA term (moving average parameter) [21].

This model allows dealing with stationary or non-stationary series, with or without seasonality [22]. The application of ARIMA involves four steps:

1. Identification: determines the parameters (p, d, q) that best fit the series;
2. Estimation: performs maximum likelihood estimation of the parameters;
3. Verification: consists in analyzing whether the chosen configuration adequately represents the behavior of the series, that is, verifying parameter fits and error correlation;
4. Prediction: forecast a number of steps ahead of the historical series based on the identified model [22].

5.3 Long Short Term Memory (LSTM) networks

Artificial neural networks are structures inspired by biological neurons, organized in layers, with the ability to gain knowledge from experience and store that knowledge through synaptic weights [23].

LSTM networks [24] are a special type of recurrent neural network (RNN) architecture, capable of learning long-term dependencies. LSTM networks were developed to deal with the problem of gradient fading and network convergence that can occur when training traditional RNN.

Due to the need for the content expansion, [24] developed the most efficient solution: long and short term memory neural networks (LSTM) [25].

Fig. 2 presents the LSTM model in memory blocks replacing traditional perceptrons, the simplest neural network model, developed in 1958 by Frank Rosenblatt. Such blocks are constructed by memory cells and some gates, which supervise the flow of information passing through the cell. Each memory cell is self-connected with linear units called Constant Error Carousels (CEC). Thus, its activation considers the state of the cell [24].

One can observe in Fig. 2 the representation of an LSTM cell, where S^t indicates the instant of the cell at instant t, X^t represents the input vector at an instant t and O^t points to the vector with the output produced also at instant t [26].

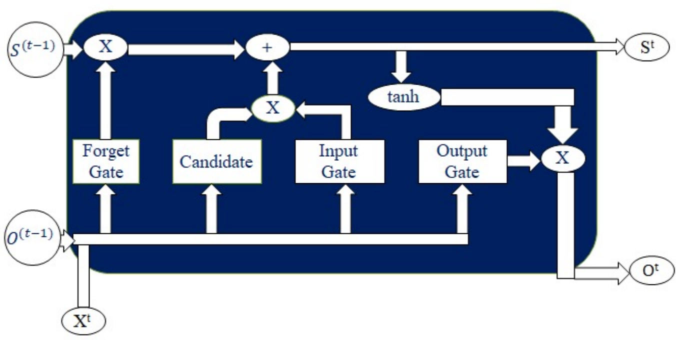

Figure 2: Representation of a memory cell of a LSTM network.

The blocks individually have one or more memory cells connected to multiplier units: at the *forget gate* the information that is no longer useful in the cell state are removed, keeping only what is considered relevant for the next step; the *input gate* adds useful information to the cell and the *output gate* sets the output values [25].

5.4 Economic evaluation

The process of migration to the FCE, as described in Section 4.3, presents the need for the initial investment for the process of adapting the MBS, according to the Distribution Procedures and the Commercialization Procedures of the National Electric System Operator (NSO), in addition to the specific legislation in force [27].

The MBS adaptation takes into consideration the needs in which the consumer's substation is located, since part of the necessary adaptations are the consumer's responsibility.

In the calculation of the economic viability for migration to the FCE, the monthly expenses with the new energy supplier and the monthly revenue of the project based on the savings obtained in relation to what was paid to the concessionaire are also included. This calculation requires the estimation of monthly consumption at the time of the contract to be signed.

6. METHODOLOGY

The proposed methodology is the construction of a pipeline to technically and economically evaluate the migration process from the Regulated Contracting Environment (RCE) to the Free Contracting Environment (FCE) from the analysis of statistical algorithms considered traditional and machine learning.

1. Verify the consumer's technical feasibility and operational cost.

   It is necessary to have contracted demand of at least 500kW to become a special consumer and of 1,000kW to become a free consumer. As a result of Ordinance 465 of the Brazilian Ministry of Mines and Energy (MME), the demand will be reduced to 500kW as of January 2023. When feasible, the migration process to the FCE can occur in the medium or long term. Opting for the freedom of negotiation, the consumer must adapt its MBS, which requires an investment, around R$ 50,000.00 for consumers in group A4. These values are proportional to the voltage level in which the installations are connected [20].

2. Obtain electricity data from this consumer, in the period of interest.

   This step consists of gathering essential data for the migration analysis: contracted and measured demand and consumption data extracted from utility bills. Ideally, it is desirable that the analyses are done with data from several years.

3. Perform data preprocessing.

   Before using the electricity data to build any predictive model, one should perform base cleaning, checking for inconsistencies, eliminating outliers, and filling in missing data. The performance of the models is highly dependent on this step.

4. Perform statistical analysis of the time series.

   The exploratory analysis of the data is carried out, which involves, among others, the quantitative analysis of the variables. This provides a basic understanding of the behavior of the data, helping in the choice of models for the following steps.

5. Build statistical forecasting models.

   The majority of models in this category is linear regression and represents the output or dependent variable as a linear combination of independent or explanatory variables, also called regressors, inputs or features. In the case of this paper, consumption is predicted from historical data of the same variable.

6. Model artificial neural networks for load forecasting.

   With the same purpose as the statistical models in the previous step, machine learning models are built to learn the patterns of a historical series of electricity consumption to predict the behavior steps ahead.

7. Analyze the performance of the models.

   The performance of the models is evaluated with error metrics, i.e., how far the predicted value is from the true value. In general, because they are non-linear models, machine learning-based models outperform classical statistical methods.

8. Evaluate the possible reduction in the cost of electricity with the proposed contracting.

   This evaluation is done with metrics based on cash flow analysis. It depends heavily on the consumption forecast obtained with the models built in the previous steps. The more accurate the forecast, the better the contractual conditions that the consumer will have when negotiating with the energy traders. As [9], buyers have difficulty in accurately forecasting their future electricity needs. So, this methodology can be a very useful guideline to help consumers in the process of migration to the free market and periodic reassessment.

7. CASE STUDY

The present work is a case study of real data from a company in the commercial area, based in the State of Rio de Janeiro, Brazil, which, unfortunately, due to a signed term of secrecy, cannot be revealed. The consumer in question is served by the energy concessionaire Light Serviços de Eletricidade S. A. with a supply voltage of 13.8 kV, and its current contracted demand is 1,400 kW and installed power of 25 MVA. At present, the consumer purchases energy in the free market.

The data was made available from April 2016 to December 2019. However, the last year (from January 2019 to December 2019) was separated for testing in order to compare the selected models, leaving only a short period, from April 2016 to December 2018, for model adjustments.

Before starting the description of the models investigated and the results obtained, a detailed statistical analysis of the time series will be performed.

7.1 Statistical Analysis

This analysis precedes time series forecasting, allowing the identification of patterns such as trend and seasonality that assist in preprocessing the data.

A time series is a collection of observations made in sequence over time, which allows a more detailed analysis of the behavior of the object under study, its characteristics, and the formulation of action plans and strategies. Series such as consumption, demand, average MegaWatt-hour (MWh) cost, bills, among others, were studied in order to predict values of energy consumption to be contracted by the consumer in question.

Fig. 3 illustrates the series of total consumption in kWh in the period under analysis, that is, from 2016 to 2019. The trend curve results from a non-parametric regression method, the locally-weighted scatterplot smoothing. The dark gray area around the line indicates a 0.95 confidence interval. Figure 4 shows the statistics per year for this series.

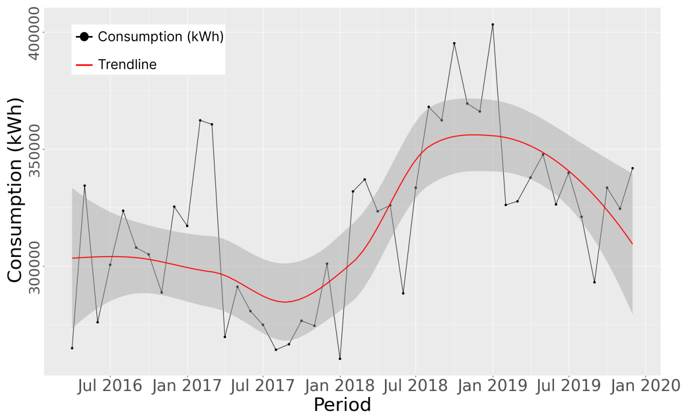

Figure 3: Total Consumption kWh series graph with trend.

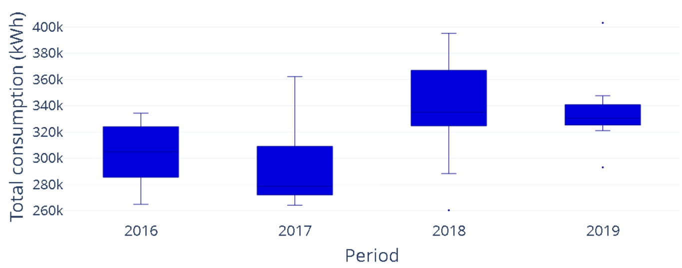

Figure 4: Box Plot of total annual consumption in kWh.

It is evident in both Fig. 3 and Fig. 4 a variation of energy consumption over the years: the year 2016 shows a growth in consumption, but in 2017 the measured energy values show a reduction compared to the previous year. The year 2018 was marked by a significant increase in consumption. In 2019, a new downward trend is observed, although with more stable values, without major variations. This can also be observed in the small height of the box in the *box-plot* relative to the year 2019, presenting, therefore, less dispersion of the data. In most years the consumption behavior is similar during the months, a higher consumption is observed at the beginning and end of the year. In this interval, the value decreases as the months go by. And finally, the presence of *outliers* in the years 2017, 2018 and 2019, accusing data outside the series pattern.

Based on the histogram in Fig. 5, a graphical analysis can be made observing the distribution of data in relation to a range of values. These data represent the monthly readings of total consumption in kWh.

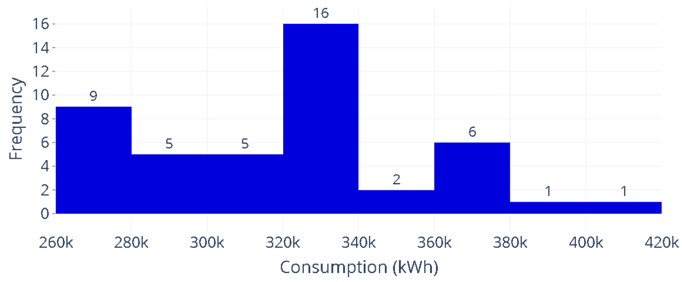

Figure 5: Histogram Total Consumption kWh.

Analyzing the graph, one can observe the highest concentration of data between the amounts of 315,000 kWh and 335,000 kWh, which ratifies the *box-plot*, given that the data of the 1st quartile (25% of readings) of 2018 and the entire interquartile box of 2019 (50% of readings) are located in this range of values.

Decomposing the series is another way to understand its behavior, prior to building the forecast models. Evaluating the trend, seasonality, and randomness components of the data, as illustrated in Fig. 6, can assist in identifying important features for defining specific structures in a neural network-based model, for example.

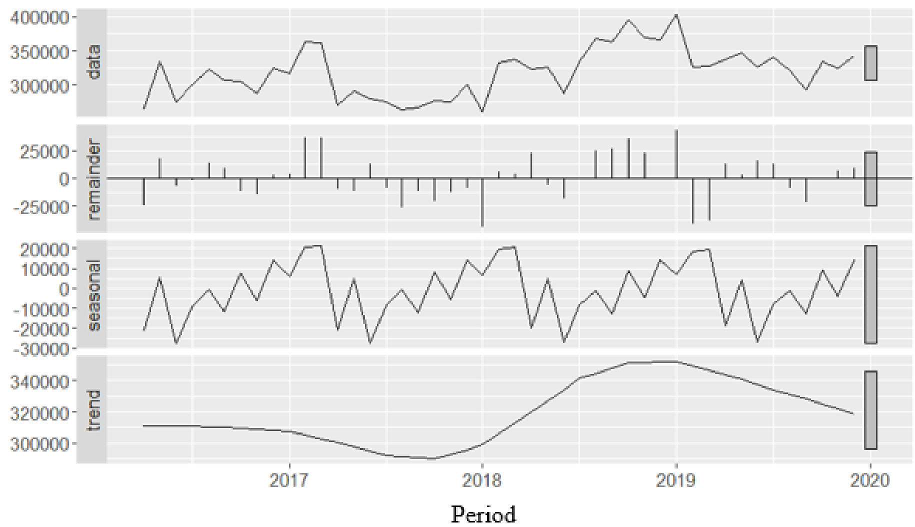

Figure 6: Decomposition of the Total Consumption series into the patterns of a time series (trend, seasonality and randomness).

Analyzing the seasonality graph one can see that the series has a variation pattern, similar between the years 2017 and 2019. One identifies a drop in energy consumption near the middle of the year and peak periods in the last and first months of the years. In addition, the series has a high level of randomness, which is manifested in the residuals plot.

7.2 Configuration of ARIMA and Long Short Term Memory (LSTM) for forecasting the energy consumption

Tab. 1 presents several parameter combinations used to build ARIMA models. The criteria for selecting the best model were BIC (Bayesian Information Criterion) and AIC (Akaike Information Criterion). It is observed that the ARIMA model (0, 1, 0)(0,1,0) was the one that best fitted the data, as it obtained the lowest values of BIC and AIC among the nineteen models tested.

This model is known as the random walk or seasonal random trend model. It assumes that the seasonal trend (difference) observed in a month is a random step away from the trend that was observed in the previous month, in that the steps are assumed to have mean zero. In other words, the expected seasonal difference in a month is the same as the seasonal difference observed in the previous month. Often time series with strong seasonal patterns do not become satisfactorily stationary by a seasonal difference alone. Hence, the seasonal random walk model will not give a good fit in these cases.

The parameters (highlighted in Tab. 1) were used for the monthly forecast of the case study consumption series over a one-year horizon. Thus, the models were fitted with data from April 2016 to December 2018. Monthly data from January to December 2019 were used for testing and evaluating the accuracy between the actual and predicted data.

In Fig. 7 one can see the predicted series in blue for both periods (training and testing) and the actual series in black. It can be seen in the graph that the two are close in the training period and more distant in the test period.

The errors obtained in the ARIMA training were 6.03% (MAPE) and 26,421.67 kWh (RMSE). In the test stage, the model presented 19.81% (MAPE) and 87,553.63 kWh (RMSE).

Learning and Nonlinear Models - Journal of the Brazilian Society on Computational Intelligence (SBIC), Vol. 21, Iss. 1, pp. 77-89, 2023

Table 1: Evaluation of ARIMA models with metrics of good fit to the data.

Model	AIC	BIC
ARIMA (0, 0, 1)(1,0,0)	788.01	794.00
ARIMA (0, 1, 1)(1,0,0)	756.41	760.81
ARIMA (0, 1, 0)(0,1,0)	476.05	477.05
ARIMA (0, 1, 1)(0,1,0)	477.31	479.30
ARIMA (1, 1, 0)(0,1,0)	477.59	479.58
ARIMA (2, 1, 0)(0,1,0)	478.61	481.60
ARIMA (0, 1, 2)(0,1,0)	478.88	481.86
ARIMA (1, 1, 1)(0,1,0)	479.78	482.77
ARIMA (0, 1, 1)(1,1,0)	477.63	480.62
ARIMA (1, 1, 0)(1,1,0)	477.91	480.90
ARIMA (2, 1, 0)(1,1,0)	478.80	482.78
ARIMA (0, 1, 2)(0,1,0)	478.88	481.86
ARIMA (1, 1, 1)(1,1,0)	479.42	483.41
ARIMA (0, 1, 1)(1,1,1)	479.63	483.62
ARIMA (1, 1, 0)(1,1,1)	479.91	483.90
ARIMA (2, 1, 0)(1,1,1)	480.74	485.72
ARIMA (0, 1, 2)(1,1,1)	481.06	486.03
ARIMA (1, 1, 1)(1,1,1)	481.42	486.40
ARIMA (2, 1, 1)(1,1,1)	482.69	488.67

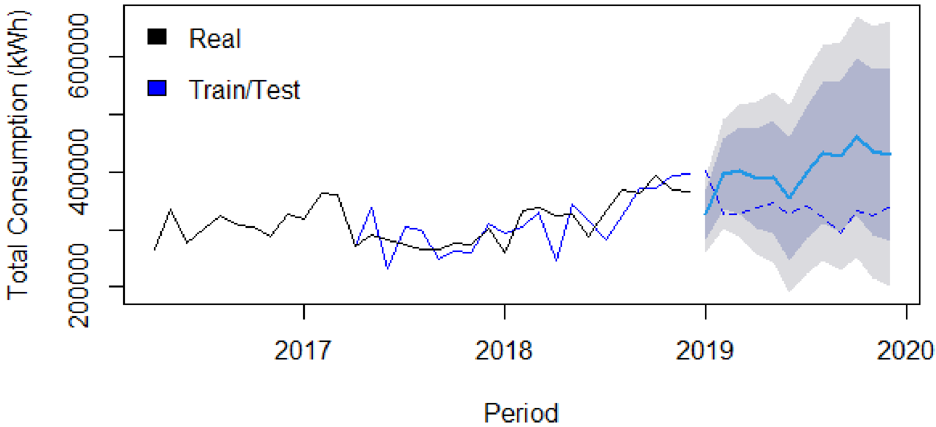

Figure 7: Graph of the forecast using the ARIMA(0, 1, 0)(0, 1, 0) model.

The first step in setting up the LSTM-type sequential model was to proportionally split the data: into 1 year for testing, 2 years for validation and the rest for training and a pre-processing step for this data, including series differentiation and data normalization.

The model used for the network was a model with two stacked LSTM layers and a dense output layer. The optimization function used was the Stochastic Gradient Descent (SGD) with a constant learning rate of 0.01, a constant decay of 1e-6, a momentum rate of 0.9, and activation function Relu, along the search for windowing, *batch size*. The number of cells for the LSTM layers were verified by *SearchGrid* method. Thus, exhaustive combinations of values for the number of cells in the first and second layers were made in order to find the best architecture among those tested. Tab. 2 presents only a sample of the configurations evaluated. However, the study should be deepened, considering the combination of other hyperparameters set in this work, in order to try to improve the performance of the models.

For this the language *Python* 3.8.2 with libraries TensorFlow 2.3.1 and Keras 2.4.3.

The configuration of the number of cells per layer was performed in order to minimize the RMSE and MAPE errors, obtained with the validation set. Tab. 2 presents 20 of the best architectures obtained along with their respective parameters and results.It is noteworthy that the size of the *batch size* attribute of the model was maintained in 6 of the evaluations performed.

The architecture that best approximates the predicted series to the actual series, with respect to the parameterizations presented, has 10 and 5 cells in the first and second hidden layers (highlighted in Tab. 2), respectively. Fig. 8 presents the model forecast result with this configuration for the validation period and Fig. 9 represents the test between January and December 2019. This was the configuration that showed the lowest error during the LSTM network validation process, with a MAPE equal to 0.9460%, and an RMSE equal to 5,096.03. The Tab. 3 presents the predicted months with the amount of consumption, as well as the average value per hour and in the month.

Table 2: Results of the LSTM prediction model.

Num. of cells in the first hidden layer	Num. of cells in the second hidden layer	RMSE (validation)	MAPE % (validation)	RMSE (test)	MAPE % (test)
10	1	9174.849	2.3088	24422.322	7.0783
5	5	5543.764	1.3760	12783.986	3.6610
10	5	5096.028	0.9460	12819.090	3.6220
20	5	6859.234	1.8052	33448.054	9.4001
30	5	14644.830	3.5890	45239.882	12.7192
20	10	5192.997	1.4390	22503,882	6.5450
30	10	7191.714	1.9320	11979.152	3.4750
40	10	5548.214	1.2800	52427.960	3.8749
50	10	15518.137	1.2120	56355.329	3.7745
100	10	7446.155	1.9083	18902.030	5.4902
120	10	5381.335	1.4048	15402.583	4.4657
130	10	5504.081	1.4481	15257.135	4.3806
140	10	8190.044	2.0576	22586.645	6.5812
30	20	5121.678	1.3175	15485.451	4.4865
40	20	5884.529	1.5781	16415.747	4.8059
50	20	4624.865	1.2696	14784.697	4.1772
60	20	5191.496	1.3546	16702.027	4.8631
70	20	5075.622	1.1184	9999.661	2.5726
80	20	4932.066	1.1050	29208.454	8.2290
90	20	4978.989	1.1770	38270.838	10.6900

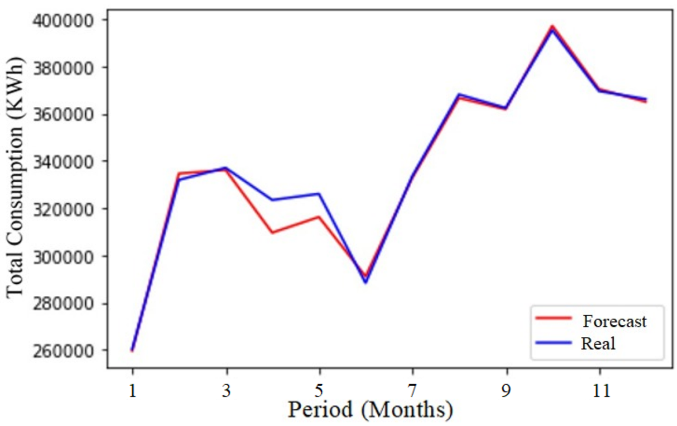

Figure 8: Validation graph (2017-2018) of the LSTM model with 10 cells in the first hidden layer and 5 cells in the second.

Table 3: Results of the forecasts for the year 2019.

Months	Consumption (MWh)	Days	Hours	Average MW/h	Average MW/month
January	260.33	31	744	0.35	260.33
February	331.87	28	672	0.49	331.87
March	336.99	31	744	0.45	336,99
April	323.38	30	720	0.45	323.38
May	325.99	31	744	0.44	325.99
June	288.30	30	720	0.40	288.30
July	333.45	31	744	0.45	333.45
August	368.02	31	744	0.49	368.02
September	362.09	30	720	0.50	362.09
October	395.21	31	744	0.53	395.21
November	369.44	30	720	0.51	369.44
December	366.04	31	744	0.49	366.04

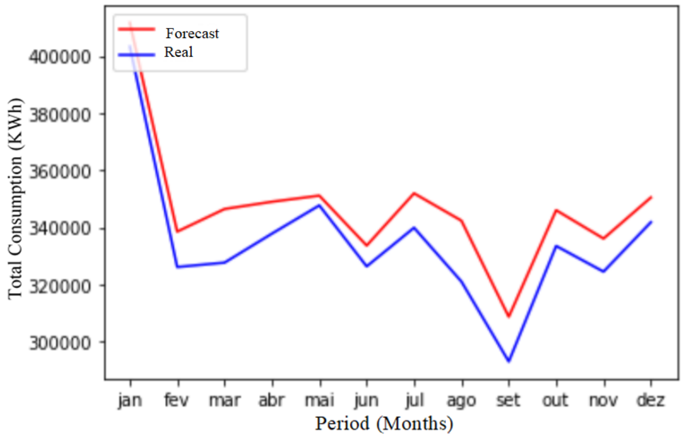

Figure 9: Test graph (2018-2019) of the LSTM model with 10 cells in the first hidden layer and 5 cells in the second.

Comparing both forecasting models, one notices the superior efficiency of the LSTM model compared to the ARIMA. The LSTM obtained lower errors and followed well the peaks and valleys of the series, unlike the ARIMA, as expected because it is a random walk model.

The LSTM configuration for 10 cells in the first hidden layer and 5 cells in its second layer presented the best result, obtaining a MAPE = 0.9460% and RMSE = 5,096.028; during the validation process of the model based on neural networks. On the other hand, the ARIMA(0,1,0)(0,1,0) model obtained in its training a MAPE = 6.03% and a RMSE = 27,662.30; which shows the greater flexibility of the LSTM network in adjusting to the data.

7.3 Economic analysis

For the economic-financial analysis the following traditional indicators will be used: Net Present Value (NPV), Internal Rate of Return (IRR) and the *Payback* period.

In the NPV calculation, the amounts billed over the study months will be used, starting in April 2016 and ending in December 2019, for both FCE and RCE. The differences between the energy bills of these two environments will be added to the initial investment amount stipulated for the migration, constituting the project's cash flow.

In order to define the Minimum Rate of Attractiveness (MRA) for the NPV calculation, the Special System for Settlement and Custody (SSSC), also known as the economy's basic interest rate, was used as a base. In 2016 the SSSC reached the value of 14.02% p.a., the year in which the investment for the market migration was made. The SSSC rate target for 2020 is 3.02% p.a., a much lower amount than in previous years. And in 2015, prior to the year of migration from RCE to FCE, the rate reached the value of 13.27% p.a. After analyzing the history of recent years, shown in Fig. 10, the value of the MRA of 14% was the most conservative for the time of the investment[2].

Figure 10: SSSC rate variation.

Based on the FCE invoice values, from April/2016 to December/2019, and simulated in the RCE by the Follow Energy portal, from the ENGIE Brazil company, it was possible to calculate by the NPV method using a MRA of 14% p.a., which is equivalent to 1.17% p.m., and an initial investment of R$ 50,000.00. Results are shown in Tab. 4. These financial indicators demonstrate that the migration of the consumer to the FCE would be very advantageous, if it were in the RCE. Generally, the consumption profile of a consumer in the captive market is analyzed to evaluate the viability of migration to the free energy market. In our project, the objective was to show the savings obtained from a consumer who was already in the free market.

[2]https://www.bcb.gov.br/controleinflacao/historicotaxasjuros

Table 4: Results obtained for the economic analysis.

Contract Period	April/2016 to December/2019
Sum Present Values (months)	R$ 2,597,928.59
Project NPV	R$ 2,547,928.59
Internal Rate of Return (IRR)	121.66%
Profitability Index	51.96
Payback Time	0.91 month

8 CONCLUSION

In this work, technical and economic-financial requirements analyses were performed for a consumer migrated in 2016 to the Free Contracting Environment (FCE). Originally in the Regulated Contracting Environment (RCE), subgroup A4 and green tariff mode, it was shown the savings that the consumer would obtain if he had not yet migrated to the FCE. This analysis considered the historical series of consumption, in the period from April 2016 to December 2019.

After analyzing the consumption statistics, forecasts were made of this series, fundamental in the process of migration to the FCE, because the amount of contracted energy avoids overspending and the non-supply of energy during the term of the contract, with a possible exposure to the DSP. The LSTM model outperformed the ARIMA model. The best configuration of the LSTM model presented a MAPE of 0.946% during the validation process, against a MAPE of 6.03% for the ARIMA model. The forecast with less error guarantees the negotiation of contracts with less flexibility margin and, therefore, better prices with the energy supplier.

The economic-financial analysis showed that the migration process was advantageous. The return on investment was obtained in less than a month, according to the *Payback* time, totaling a net present value of R$ 2,547,928.59. This amount represents 22.4% in savings, during the period of activity in the FCE, using a discount rate of 14% p.a.

As future work we propose to assess the feasibility of turning the customer into a generator of energy from renewable sources, compared to current conditions in the face of the water crisis.

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