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RESEARCH ARTICLE

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MODELING THE COMMERCIAL ELECTRICITY DEMAND IN SANTA CATARINA, USING THE BOX-JENKINS METHODOLOGY

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ABSTRACT

The present study was carried out to make forecasts of the monthly commercial electricity demand in the state of Santa Catarina. Historical data from January 2004 to December 2019 were used, with data from the last year being considered in the model validation process. After the exploratory analysis based on descriptive measures, graphs and hypothesis tests, several other techniques were employed in the various stages of the Box-Jenkins methodology: identification, estimation, diagnosis and forecast. The SARIMA (1,1,1) (1,1,1)12 was selected as the one with the best performance according to some goodness-of-fit measures. In this model process, we identify some issues in the stationarity tests and in the use of both autocorrelation and partial autocorrelation functions used in the model identification. Nonetheless, other techniques, such as maximum likelihood estimation process, Ljung-Box, Jarque-Bera and ARCH for diagnostics and RMSE, MAPE and MAE as goodness-of-fit measures performed reasonable well, as expected. Only a few parameter values (zero up to three) of the Box-Jenkins models were considered in the model estimation stage. Practical implications: The fitted model can be used to provide electricity demand forecasting in the state of Santa Catarina, that may assist the planning of the electricity sector. Further, it may be used as subsidies on the development and improvement of public policies given that there is a great. In addition to fitting a proper model to represent the monthly commercial electricity demand in the State of Santa Catarina, we have identified some drawbacks in the applied methodology. Further studies may be performed to provide a better methodology and/or approach in order to obtain better and more accurateforecasts.

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INTRODUCTION

Considering that electricity consumption per capita is directly related to the economic development of a region (Khraief et al., 2016) and that electricity is one of the most used and versatile sources of energy (ANEEL, 2002), the planning of its production, distribution, and transmission becomes very relevant. In this planning, the analysis of its demand assumes an important role. According to Fogliatto et al. (2005), demand forecasts play an important role in several areas in the management of organizations, as well as being essential in the operationalization of different aspects of operations management. Silva et al. (2012) point out that, in a context of strong growth in energy consumption, in addition to growing concern about sustainability and limitations in the capacity to expand the generation infrastructure, analyzing the demand structure of the main classes of consumers is very relevant for providing subsidies to energy planning and formulation of public policies for the sector. For Tolmasquim (2015), one of the fundamentals of a country's economic sustainability is its ability to provide logistics and energy for the development of its production safely and under competitive conditions, in addition to being environmentally sustainable. Energy storage is extremely difficult for technical and economic reasons, which is why its production must always be very well adjusted to its demand. According to Elamin and Fukushige (2018), the financial costs of forecasting errors are high, even if in small percentages, which justifies carrying out

research to propose methods and techniques that make it possible to reduce them. Thus, the modeling and forecasting of electricity demand is an extremely important resource in the planning of this sector, in which the various time series analysis techniques can be applied, aiming to identify structures and patterns of behavior of electricity demand, and thus building models that can generate accurate forecasts and assist in decision making (Pontes, 2018). Debnath and Mourshed (2018) classified the various techniques already used in modeling electricity demand in statistics, mathematics, computational, or hybrids, showing that, among the statistics, the models obtained by the Box-Jenkins methodology are more frequent. In this case, when the presence of seasonality is identified, the seasonal autoregressive integrated moving average model (SARIMA) can be used. For Hyndman and Athanasopoulos (2020), the identification of seasonality is an important marker in the choice of the forecast model. Chabouni et al. (2020) point out that the seasonality of energy demand is an important component used in short-term forecasting, which involves the control and programming of the energy system. In the study developed by Marcjasz et al. (2019), the author concluded that the inclusion of a seasonal component helped the long-term forecasts, enabling more accurate results. Li et al. (2018) concluded that the seasonal variation has significant effects on several demand aspects, such as values and moments of the occurrence of maximum load.
Thus, the main aim of this paper is to model the monthly commercial electricity demand in the state of Santa Catarina/Brazil, which may provide subsidies for the sector's strategic planning. According to Dorouche and Anschau (2015), Brazil holds one of the largest hydroelectric potentials globally, with its energy matrix composed predominantly of this source, with the rest being distributed among the other sources of generation: wind, solar, and thermal. The use of this potential requires planning, including a formal analysis of its demand. In addition, the application of some techniques used for the Box-Jenkins methodology was critically analyzed to identify possible strengths and weaknesses.

THE MODEL

An autoregressive moving average process with order p and q, denoted by ARMA (p, q), is defined by

$$X_t - \mu = \sum_{i-1}^{p} \emptyset_i (X_{t-i} - \mu) + \sum_{j-0}^{q} \theta_j \varepsilon_{t-j},$$

where X_t is the tth value observed $(t = 1,2,..,T)$, μ is the process average, i is the lag of the autoregressive process $(i = 1,2,\ldots,p)$, j is the lag of the moving averages process $(j = 1,2,\ldots,q)$, $\emptyset_i$ is the coefficient associated to the autoregressive portion in the ith lag, θ_j is the coefficient associated to the moving averages in the jth lag and $\varepsilon_t \sim R\ \ (0;\ \sigma^2)$ is the error in the tth time.
Using the lag operator B ($B^k X_t = X_{t-k}$), this expression can be rewritten as

$$\phi_p(B)\tilde{X}_t = \theta_q(B)\varepsilon_t,$$

where $\tilde{X}_t = X_t - \mu$, $\phi_p(.)$ and $\theta_q(.)$ are polynomials of degrees p and q, respectively, with B as the variable.If μ = 0, $\tilde{X}_t = X_t$then

$$X_t = \theta_q(B).\phi_p^{-1}(B)\varepsilon_t = \sum_{K-0}^{\infty} \psi_K \varepsilon_{t-K},$$

which represents the passage of a white noise process, characterized as being a stationary process, by a linear filter. Considering that the filter is stable, its output must also be stationary but with dependency relations. The methodology in question must then be used in stationary processes or transformed into stationary processes. Nonetheless, homogeneous non-stationary processes can easily be transformed into stationary processes by determining successive differences. Thus, if $\Delta^d X_t$, in which Δ represents the difference between consecutive values of the analyzed series, follow an ARMA model (p, q), we have

$$\phi_p(B)\Delta^d X_t = \theta_q(B)\varepsilon_t.$$

Therefore, it is possible to say that X_t follows an autoregressive integrated moving average process, ARIMA (p, d, q), where d is the number of differences needed for the process to become stationary. In processes that present seasonality, that is, that repeat a certain type of behavior in seasonal periods (semesters, quarters, months, weeks, ...), this modeling can be complemented with the modeling of this seasonality, analyzing data sequences with intervals determined by the size of the seasonality considered. For instance, for a free series of the monthly seasonal component, a seasonal difference of order 12 is taken, i.e.

$$Y_t = \Delta^1\ X_t = (1 - B^1\ )X_t.$$

A seasonal autoregressive integrated moving average (SARIMA) process of order $(p,d,q)(P,D,Q)_S$, that is, SARIMA $(p,d,q)(P,D,Q)_S$ is given by

$$\phi_p(B)\Phi_P(B^S)\Delta^d\Delta_S^D X_t = \theta_q(B)\Theta_Q(B^S)\varepsilon_t,$$

where $\phi_p(B)$is the autoregressive operator of order p of the non-seasonal part; $\Phi_P(B^S)$is the autoregressive operator of order P of the seasonal part; Δ is the difference operator; d is the number of differences used in the non-seasonal part; D is the number of differences used for the seasonal part; X_t is the t th value observed; $\theta_q(B)$ is the operator of moving averages of order q of the non-seasonal part; $\Theta_Q(B^S)$is the operator of moving averages of order p of the seasonal part, and s is the number of periods in the seasonal part. To carry out modeling with this methodology, the stochastic process must be stationary and ergodic. A stochastic process is called weakly stationary or second-order stationary if its mean and variance do not vary over time. The covariance value between two periods depends only on the degree of lags between observations and not on the effective period in which the covariance is calculated. According to Bueno (2011), this means that the process presents: $E(X_t) = \mu \forall t$; $E|X_t^2| < \infty$;and $c\ (X_t, X_{t-j}) = \gamma_j$.

Besides the graphical methods, analytical methods can assess stationarity, including the augmented Dickey Fuller (ADF) test (Dickey and Fuller, 1981), one of the most used in the literature. Several tests have already been proposed to verify the null hypothesis that the stochastic process has a unitary root, being non-stationary, whose performance depends on some properties of the analyzed stochastic process, such as the presence of structural break. Among them are the non-parametric PP test, proposed by Phillips and Perron (1988), the ADF-GLS test, proposed by Elliot et al. (1996), and the ZA test, proposed by Zivot and Andrews (1992), among others. When there is seasonality, the test should be applied twice: initially, it evaluates stationarity of the non-seasonal part and, later, of the seasonal part. A stochastic process is said to be ergodic if $\underline{yp} \rightarrow E(y_t)$

and $\hat{\gamma}_j p \to \gamma_j$. This means that the sample moments must converge in probability to the population moments. According to Hamilton (1994), this property is verified in a stochastic process for the first moment if the sum of the covariance is finite, that is, $\sum_{j-0}^{\infty}|\gamma_j| < \infty$. Bueno (2011) draws attention to the fact that, in practice, stationarity and ergodicity have the same requirements.

THE ANALYZED CONTEXT

According to IBGE (2020), the state of Santa Catarina has a territorial extension of 95,730.684 km², with an estimated population of 7,252,502 individuals, resulting in a demographic density of 65.29 inhabitants/km², much higher than that of Brazil, which is 22.43 inhabitants/km². According to NECAT (2019), its human development index (HDI) is 0.674, which is also higher than that of Brazil, 0.612. The average per capita income in this state was R$ 1769.00 in 2019. Santa Catarina, along with Rio de Janeiro, Amapá, Goiás, São Paulo, and Amazonas, is considered an urban state, as the entry into the urban area represented more than 90% of the total migratory flow (MME, 2007). According to GESC (2019), Santa Catarina's economy is quite diversified and has several hubs in several regions. In the north, for example, there are the technological, furniture, and metal-mechanic hubs; in the south, there are activities associated with the coal exploitation, in addition to cold storage and ceramic poles; industries in the textile sector are concentrated in the Itajaí Valley Region, while pig farming is an important activity in the west. Tourism is another important point in Santa Catarina's economy, especially on the coast (MME, 2007; GESC, 2019). According to SEBRAE (2010), the tertiary sector, encompassing the trade and service sector, is the fastest growing globally, accounting for 65.8% of the national GDP in Brazil. In Santa Catarina, until 2010, this sector was responsible for approximately 80% of companies in the state, accounting for about 47% of formal jobs. For this whole context to work, there is a need for energy. In this state, the electricity generation and distribution are in charge of the company CentraisElétricas de Santa Catarina (CELESC), which, according to GESC (2017), in 2017, served about 93% of the Santa Catarina territory, in addition to the municipality of Rio Negro/Paraná. Its concession area, which corresponds to 1.1% of the country's geographic area, currently comprises just over 3 million consumer units. According to CELESC (2020), this company is structured as a holding company, consisting of two subsidiaries: one responsible for energy generation and the other for its distribution. It also maintains a controlling interest in SCGAS and participates in other related companies (Figure 1).

Figure 1. Composition of CELESC holding - Source: CELESC (2020)

In MME (2007), an analysis of the socioeconomic and energy development that occurred in Brazil in the period 1970-2004 was carried out. It led to the conclusion that the economic and energy contexts showed great proximity.

METHODOLOGY

The study of the monthly commercial electricity demand was carried out for Santa Catarina/Brazil, from January 2004 to June 2019, with 2019 being used to validate the models found. The data were obtained from the Energy Research Company (EPE, 2020). Following studies in the area, it was assumed that all energy demand is effectively supplied. Initially, seasonality was analyzed, which was done through graphical methods, such as general line graph and by seasonality period, and analytical methods, such as descriptive measures and hypotheses tests (analysis of variance with blocks and Friedman). Upon verifying its presence, the SARIMA model was selected from those made available by the Box-Jenkins methodology to model this variable. Further, following most of the studies developed on modeling the demand for electricity, such as Silveira and Mattos (2017) and Nunes (2019), logarithmic transformation was used to attenuate any heteroscedasticity problems, common in this type of data. The stationarity of the series was assessed using the augmented Dickey-Fuller (ADF) test, analyzing the model situation with constant and trend, only with constant and none of them. The maximum number of lags was defined according to Schwert (1989) and when rejecting the null hypothesis, stationarity is assumed. If no evidence of stationarity was found for level data, the same procedure was performed for the first difference and so on until it was detected, which was performed separately for the non-seasonal and seasonal parts. In both cases, the Bayesian information criterion (BIC), proposed by Schwarz (1978), was used to help choose the number of lags to be considered. The KPSS test (Kwiatkowski et al., 1992) was used to confirm the stationarity of the non-seasonal part and the HEGY test (Hylleberg et al., 1990) to confirm the stationarity of the seasonal part. Although graphs of the autocorrelation function and partial autocorrelation function are normally used to select probable values of p, q, P, and Q, in this study all possible combinations of values of these parameters between zero and three were evaluated, totaling 256 models, avoiding a possible subjectivity in graphic interpretation. Again, the BIC statistic was used to identify, among these, 5% of the most parsimonious models, resulting in 12 or 13 candidate models. The estimation of the coefficients of the candidate models was carried out using the maximum likelihood method. Again, the BIC value was used to create a hierarchy among them according to their parsimony. In all residuals, the following characteristics were evaluated: independence by the Ljung-Box test (Ljung and Box, 1978), normality by the Jarque-Bera test (Jarque and Bera, 1987), and homoscedasticity by the ARCH test (ENGLE, 1982).

Models that did not present independent residues were eliminated. Next, the selected models were validated based on the forecasting errors, using the measures: mean absolute error (MAE), root mean square error (RMSE), and mean absolute percentage error (MAPE), in addition to the Theil's U, to identify the best forecasting model. In case of divergence between these indicators, confidence intervals were used. In the inferential analyses, the significance level of 0.01 was considered, and the interval estimates were performed with a confidence level of 0.95. More information on these techniques can be found in Box and Jenkins (1976), Hamilton (1994), Bueno (2011), and Hyndman and Athanasopoulos (2020). The described procedures were performed in the R software (R CoreTeam, 2020), using the forecast (Hyndman and Khandakar, 2008), urca (Pfaff, 2008), tseries (Trapletti and Hornik, 2019), seasonal (Sax and Eddelbuettel, 2018), aTSA (Qiu, 2015), and lmtest (Zeileis and Hothorn, 2002) packages, among others.

RESULTS

The monthly commercial electricity demand in the state of Santa Catarina, from January 2004 to December 2019, varied between 142,886 MWh and 435,692 MWh, concentrating around the average of 267,976 MWh, with a standard deviation of 71,640 MWh. Its distribution can be considered symmetrical, as its skewness was 0.15, and with light tails, as the kurtosis coefficient was -0.97.
The graph in Figure 2 shows the presence of seasonality, which is confirmed by the Friedman test $\chi^2 = 154{,}62; g = 11; = 2{,}2\,x10 - 16$.

Paired Wilcoxon tests identify the similarity between the months of the December-April period and the June-October months. Non-parametric tests were used depending on the data properties. In the stationarity analysis performed in the transformed series, the ADF test considered the non-seasonal part of the stationary series as the first difference for a model with trend and constant ($\tau_c = -3{,}99$; $\tau_{c.} = -8{,}43$), which was confirmed by the KPSS test, the same happening for the seasonal part, but considering only the constant ($\tau_c = -3{,}46$; $\tau_{c.} = -3{,}74$), which was confirmed by the HEGY test. Figure 3 presents the autocorrelation and partial autocorrelation functions for the non-seasonal (Panels a and b) and seasonal (Panels c and d) parts, suggesting a model of moving averages of order 1, both for the non-seasonal and the seasonal part. However, as highlighted in the Methodology Section, the modeling was carried out for all possible combinations between zero and three for the parameters p, q, P, and Q of the SARIMA model. The BIC values allowed the identification of the 5% most parsimonious models presented in Table 1, along with the results of the Ljung-Box, Jarque-Bera, and ARCH tests applied to their residues.

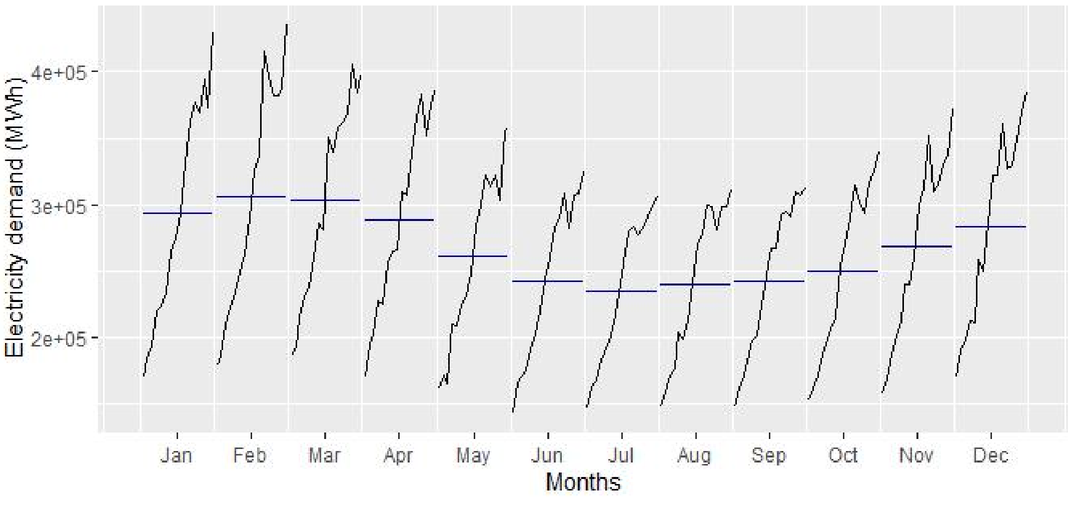

Figure 2. Monthly commercial electricity demand, Santa Catarina, 2004-2019

Table 1 - BIC information criterion and p_v the Ljung-Box, Jarque-Bera, and ARCH tests of the candidate models, SC, 2004/18

Models	BIC	p_v		
		Ljung-Box	Jarque-Bera	ARCH
SARIMA (0,1,1) (0,1,1)12	-572.32	0.0415	0.0826	0.3849
SARIMA (1,1,1) (0,1,1)12	-569.06	0.1331	0.1563	0.3704
SARIMA (0,1,2) (0,1,1)12	-568.99	0.1267	0.1551	0.3682
SARIMA (0,1,1) (1,1,1)12	-568.43	0.0658	0.0738	0.3346
SARIMA (0,1,1) (0,1,2)12	-568.26	0.0603	0.0752	0.3411
SARIMA (0,1,2) (0,1,2)12	-564.36	0.1092	0.1295	0.3407
SARIMA (1,1,1) (1,1,1)12	-564.49	0.1105	0.1251	0.3421
SARIMA (0,1,2) (1,1,1)12	-564.45	0.1082	0.1241	0.3396
SARIMA (1,1,1) (0,1,2)12	-564.41	0.1121	0.1305	0.3433
SARIMA (0,1,1) (0,1,3)12	-564.06	0.1144	0.0794	0.3120
SARIMA (0,1,3) (0,1,1)12	-563.96	0.1324	0.1516	0.3682
SARIMA (2,1,1) (0,1,1)12	-563.95	0.1345	0.1541	0.3706
SARIMA (1,1,2) (0,1,1)12	-563.95	0.1341	0.1549	0.3706

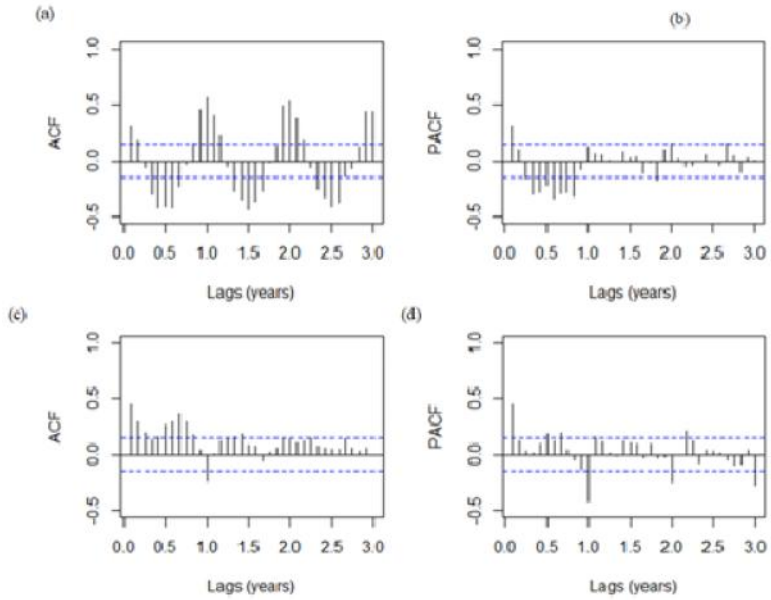

Figure 3. Autocorrelation functions of the (a) non-seasonal part and (c) seasonal part, and partial autocorrelation functions of the (b) non-seasonal part and (d) seasonal part

The results in Table 1 indicate that, at the 0.01 significance level, there are no evidences that the residuals present autocorrelation, normality deviations, and heteroscedasticity, which is why none of the fitted models were eliminated. It was observed that in the composition of the 13 candidate models, there was a higher frequency of random shocks in relation to past values, both in the non-seasonal and in the seasonal part

Table 2 shows the accuracy measures (RMSE, MAE, MAPE and Theil's U) of the forecasts used to validate the models selected as candidates. Three models were selected: SARIMA (1,1,1) (1,1,1)12 for presenting the lowest RMSE, SARIMA (1,1,1) (0,1,2)12 for presenting the lowest MAE and SARIMA (0,1,1) (0,1,2)12 for presenting the lowest MAPE and Theil's U values. Complementing the analysis, 95% confidence intervals were built for the 12-month forecasts for 2019, for these three models.

Table 2. Validation of candidate models for forecast, SC, 2019

Model	RMSE (MWh)	MAE (MWh)	MAPE (%)	Theil's U
SARIMA (0,1,1) (0,1,1)12	15,167.8	11,822.2	3.1480	0.5006
SARIMA (1,1,1) (0,1,1)12	14,907.8	11,721.4	3.1276	0.5002
SARIMA (0,1,2) (0,1,1)12	14,931.0	11,733.5	3.1302	0.5013
SARIMA (0,1,1) (1,1,1)12	14,440.7	11,631.5	3.0930	0.4914
SARIMA (0,1,1) (0,1,2)12	14,485.1	11,586.0	3.0778*	0.4880*
SARIMA (0,1,2) (0,1,2)12	14,931.0	11,733.5	3.1302	0.5013
SARIMA (1,1,1) (1,1,1)12	14,408.1*	11,583.1	3.0852	0.4910
SARIMA (0,1,2) (1,1,1)12	14,412.9	11,589.6	3.0866	0.4917
SARIMA (1,1,1) (0,1,2)12	14,452.2	11,569.1*	3.0805	0.4889
SARIMA (0,1,1) (0,1,3)12	15,095.5	12,322.6	3.3166	0.5412
SARIMA (0,1,3) (0,1,1)12	14,904.2	11,711.8	3.1245	0.4990
SARIMA (2,1,1) (0,1,1)12	14,903.8	11,719.7	3.1273	0.4998
SARIMA (1,1,2) (0,1,1)12	14,905.1	11,720.7	3.1276	0.5000

Note –(*) Indicates the lowest value.

Finally, the model selected was SARIMA(1,1,1) (1,1,1)12 for not presenting observed values exceeding the limits of the respective confidence intervals (Table 3).

Table 3. Observed and predicted values of the SARIMA (1,1,1) (1,1,1)12 model and their respective confidence intervals, SC, 2019

Months	Observed(MWh)	Forecast(MWh)	CI 0.95 (MWh)	
			LI	LS
January	428,643.79	396,575.4	366,632.9	428,963.3
February	435,691.70	411,720.9	378,776.5	447,530.6
March	396,423.49	408,670.8	374,862.2	445,528.7
April	385,777.65	388,111.1	355,046.5	424,255.0
May	357,954.88	348,106.9	317,625.2	381,513.8
June	324,249.35	324,983.6	295,780.1	357,070.5
July	306,071.70	314,506.3	285,542.5	346,408.2
August	311,205.36	322,310.0	291,927.7	355,854.3
September	312,157.83	325,896.1	294,486.6	360,655.8
October	338,895.27	334,943.2	301,970.9	371,515.7
November	371,183.61	357,374.2	321,474.3	397,283.1
December	384,836.05	378,079.6	339,355.8	421,222.3

The residuals (Figure 4) of the selected model are concentrated around its mean (-0.0038), with a standard deviation of 0.038, varying between -0.1112 and 0.1176. The distribution is symmetrical, as its skewness coefficient is 0.0056, and presents heavy tails, as its kurtosis coefficient is given by 0.70(i.e. it has a leptokurtic distribution). Hence, the SARIMA(1,1,1) (1,1,1)12 model presents a reasonable fit to these data.

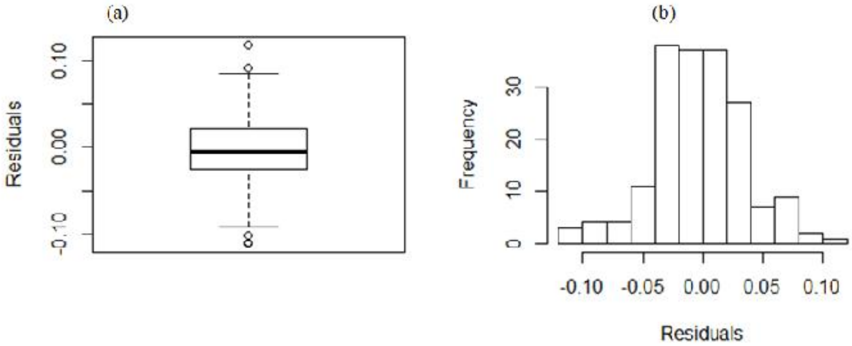

Figure 4. (a) Box plot and (b) histogram of the residuals from the SARIMA(1,1,1) (1,1,1)12 model

The coefficients and their respective significance and standard errors of the selected model are given in Table 4, while their graphical representation and forecasts for 2019 are shown in Figure 5.

Table 4. Estimates of the coefficients of SARIMA (1,1,1) (1,1,1)12

Parameters	Estimate	Standard error	p-value
$\hat{\phi}_1$	0.1145	0.1044	< 0.01
$\hat{\theta}_1$	-0.7559	0.0620	> 0.01
$\hat{\Phi}_1$	-0.0785	0.1049	< 0.01
$\hat{\Theta}_1$	-0.8271	0.0928	> 0.01

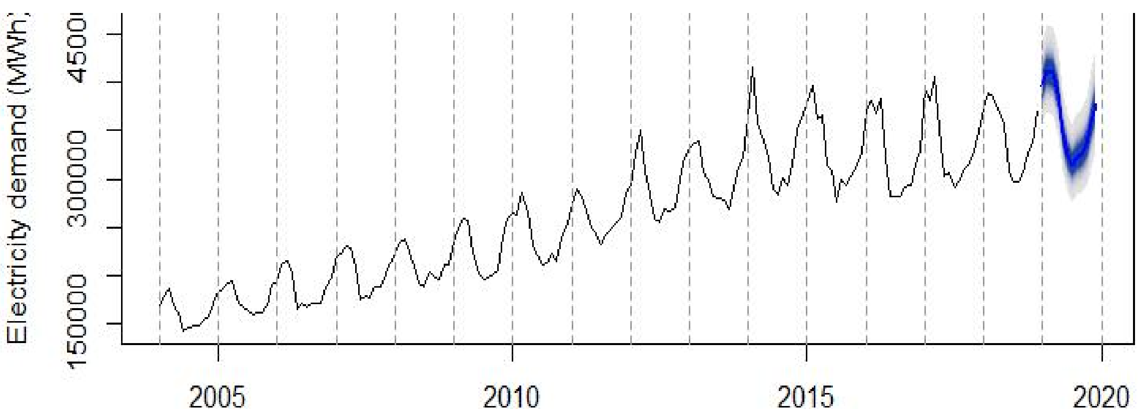

Figure 5. Monthly commercial electricity demand described by SARIMA (1,1,1) (1,1,1)12 model, Santa Catarina, 2004-2019

FINAL CONSIDERATIONS

Developing studies to model and predict the demand for electricity in a region can be an extremely important resource in managing its human, material, economic, and financial resources to guarantee the supply of the energy necessary for its development. The present study modeled the monthly commercial electricity demand in Santa Catarina, using the Box-Jenkins methodology applied to seasonal data. This technique fitted the model only from its past values and random shocks. Data on the state's historical demand were used, and the forecast horizon was 12 months. Regarding the methodology used, some limitations were found in the stationarity tests, so confirmatory tests were used. Many tests to identify stationarity in a time series have already been proposed.

Perhaps, defining a strategy relating their performances to some properties of the data would be a good idea. It also fell short of the expectations to the use of the autocorrelation function and the partial autocorrelation function in determining model orders, which is why several combinations of different values of these parameters were modeled, selecting the most parsimonious. Some candidate models were identified. It is important to identify them because the model with the best fit according to some statistical measuresmight not be the one that provides the best forecast, as can be seen in this study. The considered statistical model presented a reasonable fit based on the accuracy measures and did not present any observed value exceeding the limits of the obtained confidence intervals. However, it was not able to meet a requirement of Brazil's electric energy production sector: to present errors (the difference between demand and supply) below 3.0%, indicating that it needs to be improved. As already mentioned, the financial costs of forecasting errors are high, even in small percentages. Some analyses are being implemented to improve the statistical model performance. This study is a step in a broader analysis that is being carried out on electricity demand data in the three states in the southern region of Brazil for the three main consumer classes: residential, commercial, and industrial.

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