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ORIGINAL ARTICLE

Forecasting electricity generation from renewable sources during a pandemic

Previsão da geração de eletricidade a partir de fontes renováveis durante uma pandemia

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Abstract: Renewable sources are responsible for more than half of Brazilian electric generation, which basically correspond to hydropower, biomass and wind sources. This research aimed to verify if the Autoregressive Integrated Moving Average (ARIMA) models present good performance in predicting electricity generation from biomass, hydropower and wind power for the first months of COVID-19 pandemic in Brazil. The best forecasting models adjusted for biomass, hydropower and wind generation was the SARIMA, since this model was able to identify seasonal effects of climatic instability, such as periods of drought. Based on the seasonality of the largest generating sources, renewable generation needs to be offset by other sources, as non-renewable, and more efforts are needed to make Brazilian electric matrix more sustainable.

Keywords: ARIMA models; Renewable sources; Time series; COVID-19.

Resumo: As fontes renováveis são responsáveis por mais da metade da geração elétrica brasileira, as quais correspondem basicamente às fontes hidráulica, biomassa e eólica. A presente pesquisa teve como objetivo verificar se os modelos Autorregressivos Integrados de Médias Móveis (ARIMA) possuem bom desempenho ao prever a geração de eletricidade das fontes biomassa, hidráulica e eólica nos primeiros meses da pandemia da COVID-19 no Brasil. O melhor modelo de previsão ajustado para as fontes biomassa, hidráulica e eólica foi o SARIMA, uma vez que esse modelo foi capaz de identificar os efeitos sazonais causados por instabilidades climáticas, como períodos de estiagem. Devido à sazonalidade das principais fontes geradoras, a geração renovável precisa ser compensada com outras fontes, como as não renováveis. Dessa forma, mais esforços são necessários para tornar a matriz elétrica brasileira mais sustentável.

Palavras-chave: Modelos ARIMA; Fontes renováveis; Séries temporais; COVID-19.

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1 Introduction

Renewable sources are a competitive advantage for an electric matrix in the global energy scenario (Maciel et al., 2018). According to the International Energy Agency (IEA, 2017), the world's most renewable matrices are from Iceland, Paraguay, Democratic Republic of Congo, Albania, Ethiopia and Costa Rica. Brazilian electric matrix can be considered renewable, since hydropower is responsible for generating more than half of the country electricity (EPE, 2018). The widespread use of this source is justified by its abundance; Brazil has numerous rivers with large tributaries and substantial power generation potential (Ferreira et al., 2016).

Other renewable sources used in the country are biomass, solar and wind energy (EPE, 2018). The first one has presented great progress in research and implementation actions, as it is an alternative source that contributes to the reduction of climate change (Bakhtiar et al., 2020; Daioglou et al., 2019; Uddin et al., 2019). Even though biomass and wind sources present an unstable generation during the year, they are complementary to hydropower generation in Brazil (Cotia et al., 2019; Čepin, 2019; Ferreira et al., 2018; González-Aparicio & Zucker, 2015; Razmjoo et al., 2019; Silva et al., 2016). In addition to climatic instabilities, electricity demand can be influenced by consumer behavior, which changed significantly after the COVID-19 pandemic with the transition of several jobs to home offices (Qarnain et al., 2020; Carvalho et al., 2021). The planning of an electric matrix can be based on time series analysis, which evaluate trends, serial correlation and instabilities over time. (Kuang et al., 2016; Renn & Marshall, 2016; Shen & Ritter, 2016). Time series have already been applied to renewable energies in studies developed by Alsharif et al. (2019), Baruque et al. (2019) and Hosseini et al. (2019). Linear models, such as the Autoregressive Integrated Moving Average (ARIMA), have high levels of accuracy and can be used to reveal series average behavior (Bhutto et al., 2017). Neuro-fuzzy logic is also a method for predicting renewable generation, such as biomass, according to studies of Olatunji et al. (2019a, b).

This research gap is to predict electricity generation from renewable sources as an alternative to previous work that only predicted the market prices renewable energy (González-Aparicio & Zucker, 2015; Salles & Campanati, 2019). The objective of this research is to verify which is the best forecasting model, the ARIMA model or its seasonal version (SARIMA), and to predict electricity generation from biomass, hydropower and wind sources for the first months of COVID-19 pandemic in Brazil.

The general ARIMA models were adjusted, because we were looking for an explanation given by the current and past values of each series. Although these models do not consider the correlation among variables, they are more accurate than the vector autoregressive models (Ramser et al., 2019; Senna & Souza, 2016).

The article is structured in five sections: the first one had a brief introduction to the problem; the second one presents the methodology used; the third one contains the results; the fourth one addresses the discussions; the last one deals with the conclusions and suggestions for future research.

2 Materials and methods

2.1 Data collection

Amounts of electricity generated (GWh) from renewable sources were collected at National Electric Energy Agency open database (ANEEL, 2020). Three time series were collected to analyze biomass, hydropower and wind generation, since they are the Brazilian electric matrix renewable part. The modeling stage had 60 monthly observations, from January 2015 to December 2019, and, for out-of-sample forecasts, another 6 observations were used referring to the period from January to June 2020.

2.2 ARIMA models

To understand behavior and series generator process, Autoregressive Integrated Moving Average models (ARIMA) were applied to capture serial correlation effects, as long as the series were stationary (Morettin, 2016). The autocorrelation function (ACF) and the partial autocorrelation function (PACF) were applied to determine which ARIMA filter will be used: AR, MA, ARMA, ARIMA or SARIMA (Souza, 2016; Reichert & Souza, 2020).

As the series stationarity is a basic assumption for the ARIMA modeling, unit root tests, such as Augmented Dickey-Fuller (ADF) e Kwiatkowski–Phillips–Schmidt–Shin (KPSS) tests, were applied in series in level and in their first differences to identify the number of differences to make the series stationary (*d*=0 or *d*=1) (Kwiatkowski et al., 1992; Dickey & Fuller, 1981).

The ARIMA models and their seasonal variation (SARIMA) were applied to predict the amount of electricity generated by renewable sources (Renn & Marshall, 2016), as presented in Equations 1 and 2 (Box & Jenkins, 1970; Box et al., 1994).

$$\phi(B)\Delta^d X_t = \theta(B)e_t \tag{1}$$

$$\phi(B)\Phi(B)\Delta^d \Delta^{Ds} X_t = \theta(B)\Theta(B)e_t \tag{2}$$

where: X_t represents the series analyzed, *B* is the delay operator, *d* is the integration order, ϕ is the autoregressive parameter, Φ is the seasonal autoregressive parameter, θ is the moving average parameter, Θ is the seasonal moving average parameter and e_t characterizes the residue classified as white noise, which means independent and identically distributed values (*i.i.d.*).

The best model for each generating source was validated based on its lowest Akaike and Bayesian information criteria (AIC and BIC) values and residues with the white noise condition (Akaike, 1974; Kim et al., 2017).

2.3 Methodological steps

Initially, a chart of the series original values was elaborated to investigate the stylized factors as trend, seasonality, stationarity and fluctuations that can be understood as volatility. To confirm the series stationarity, the ADF and KPSS tests were performed and their results were used to decide whether a difference (*d*=1) would be needed to make the series stationary.

In sequence, the ACF and PACF functions were applied to the original series to verify the serial correlation and identify a possible ARIMA filter to be used in the adjustment step.

The best model was chosen based on adjustment statistics, such as AIC and BIC, and the white noise condition. After adjustment, the models were used to predict out-of-sample values in the interval between January and June 2020. The accuracy of the models was verified through Mean Absolute Percentage Error (MAPE), Symmetric MAPE, Root Mean Square Error (RMSE) statistics and the U-Theil coefficient

(Khair et al., 2017; Jadhav et al., 2017). Finally, charts of predicted and original values were used to verify the forecasting performance of the ARIMA models. These analyses, model adjustment and forecasts out-of-sample were developed in EViews S.V. 9 software.

3 Results

In initial analysis, time series charts were elaborated to verify stationarity, seasonality and volatility in electricity generation from renewable sources, as shown in Figure 1.

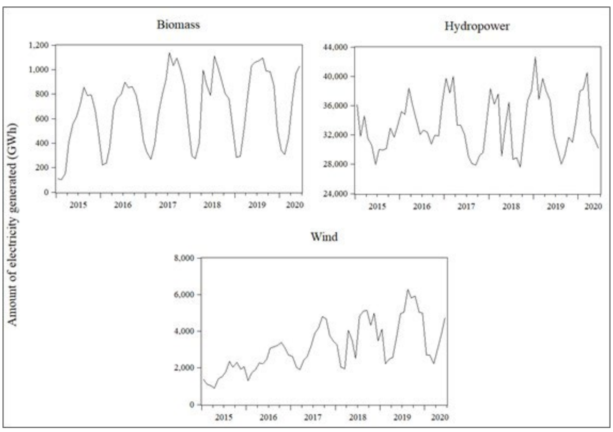

Figure 1. Timeline charts of amounts of electricity generated from renewable sources.

The biomass and wind series can be considered as non-stationary of renewable, due to the growing trend behavior (Figure 1). Otherwise, hydropower presented the most stable behavior, despite having seasonal peaks caused by climatic instability. In order to confirm the series stationarity, the ADF and KPSS unit root tests were performed with the series in level and in their first differences; the results can be seen in Table 1.

Table 1. Unit root tests results.

Unit Root Tests	ADF	KPSS	ADF	KPSS
	In level		1st difference	
Biomass	-2.07	0.29	-7.17	0.04
Hydropower	-5.83	0.08	-6.89	0.03
Wind	-1.86	0.84	-6.86	0.02

Where: for an α = 0.05, the critical values are ADF: -2.92 and KPSS: 0.46.

The tests results confirmed the non-stationarity of biomass and wind generation, as well as the stationarity of hydropower generation (d=0). The ACF and PACF charts also confirmed the need to adjust models with these series in their first differences (d=1). In this case, the biomass and wind series were transformed by applying differences.

Serial correlation could be identified by the ACF and PACF charts, which enable the application of the ARIMA models to predict electricity generation from renewable sources. In Table 2, the best ARIMA models for each renewable source are presented. These models were select based on the lowest AIC and BIC values and the white noise condition.

Table 2. The ARIMA models for renewable generation.

		Parameter	**p-value**	**AIC**	**BIC**
Biomass	SARIMA $(0,1,1)(1,0,0)_{12}$	$\theta_{12} = -0.99$ $\Phi_{12} = 1.00$	< 0.05	12.51	12.61
Hydropower	SARIMA $(1,0,0)(1,0,0)_{12}$	$\varphi_1 = 0.98$ $\Phi_{12} = 0.55$	< 0.05	18.78	18.88
Wind	SARIMA $(1,1,1)(1,0,0)_6$	$\varphi_5 = -0.45$ $\theta_1 = -0.35$ $\Phi_6 = -0.34$	< 0.05	15.78	15.92

The best-adjusted models for biomass, hydropower and wind generation were a seasonal ARIMA (Table 2), since renewable sources are directly affected by the climate. For prediction, the accuracy of the selected models was analyzed by the MAPE, Symmetric MAPE, RMSE statistics and the U-Theil coefficient applied to out-of-sample forecasts, as shown on Table 3.

Table 3. Statistics and the predicted values from the selected models for renewable generation.

Amount of electricity generated (GWh)	**Biomass**		**Hydropower**		**Wind**	
	forecast	**error**	**forecast**	**error**	**forecast**	**error**
January 2020	311.69	26.18	36250.71	17757.41	4499.54	-1813.92
February 2020	326.46	-16.58	34630.60	3629.09	3072.23	-361.92
March 2020	433.09	18.74	39589.88	934.62	2948.05	-732.81
April 2020	762.31	-2.97	39315.19	-7055.64	2645.30	393.77
May 2020	854.67	118.40	31420.68	55.87	3033.14	731.37
June 2020	1003.86	26.79	28645.24	1472.96	4543.96	189.41
MAPE	5.40		7.23		25.06	
Symmetric MAPE	5.58		6.99		21.81	
RMSE	51.73		3393.30		883.56	
U-Theil coefficient	0.04		0.05		0.13	

According to the forecast statistics, the biomass and hydropower generation models were the ones that presented the best performance. The wind generation model also achieves satisfactory performance, considering that the best-adjusted model is not always the best predictor.

For specific analysis of the forecasts, charts were elaborated to compare the predicted and original values for each generation source, as shown in Figures 2, 3 and 4.

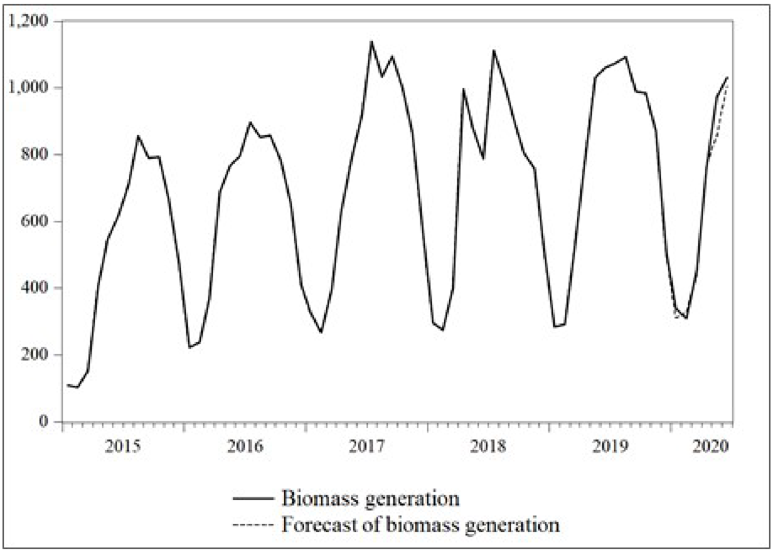

Figure 2. Forecast of biomass generation based on the seasonal ARIMA model.

In Figure 2, it is proved that the adjusted model for biomass generation was accurate, as the distance between the values is almost imperceptible in the chart. The behavior of predicted values for hydropower generation can be seen in Figure 3.

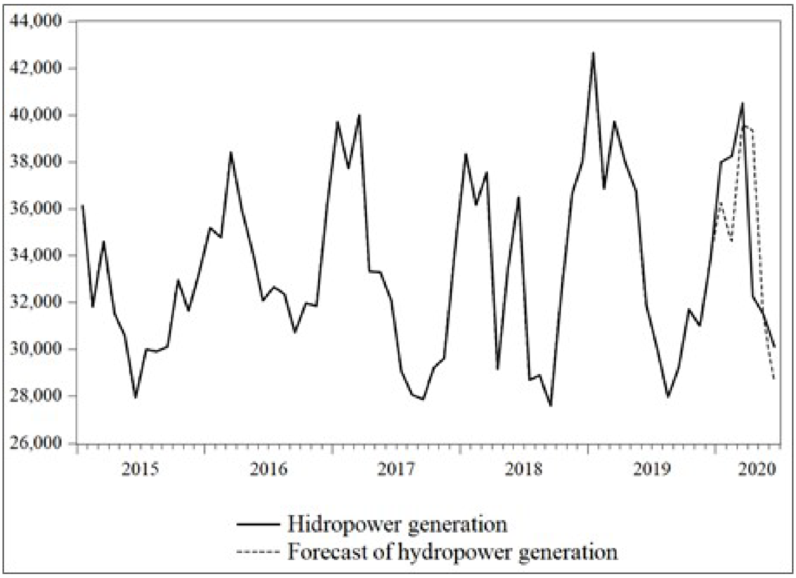

Figure 3. Forecast of hydropower generation based on the seasonal ARIMA model.

The model for hydropower generation were capable to predict seasonal peaks and some movements of the original series, since it also has shown a good performance (Table 3). The chart of predicted values for wind generation are presented in Figure 4.

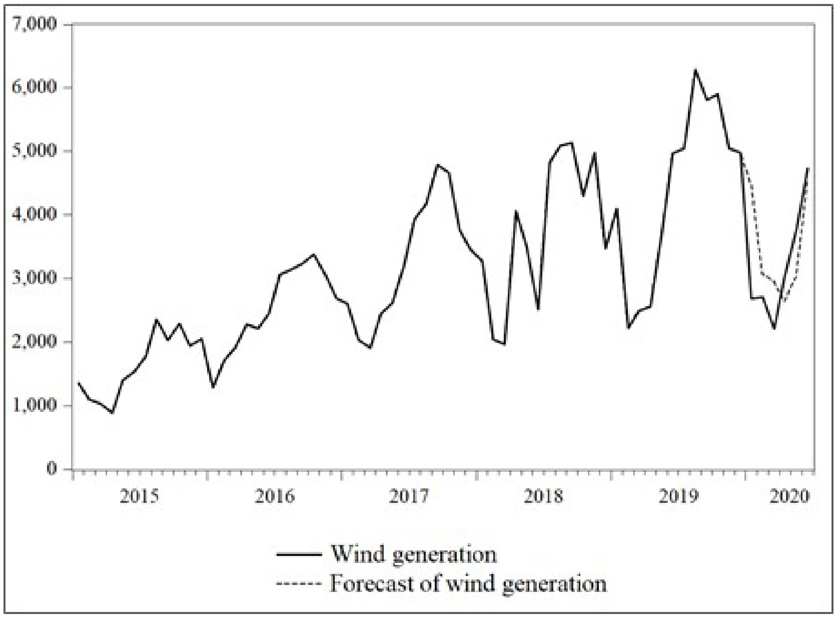

Figure 4. Forecast of wind generation based on the seasonal ARIMA model.

Although the model for wind generation has not demonstrated a good forecasting performance like the other models, this model was able to reproduce the drop in wind generation in March 2020.

4 Discussion

Renewable sources are a great option to generate electricity, but their volatility affects the stability of electrical system, since these sources are dependent on climatic factors. In conjunction with demand, climatic factors are the most critical points of a renewable matrix (Lucena et al., 2018; Pes et al., 2017). Consequently, renewable sources need to be combined to provide a stable generation (Saheli et al., 2019). For example, in Brazil, although hydropower generation is more controllable due to management of hydroelectric dams during drought periods, it is offset by biomass, coal, fossil fuels, natural gas, nuclear, solar and wind power (Galvão & Bermann, 2015; Silva et al., 2016).

According to other studies, volatility models show good performance in predicting energy generation from renewable sources (Shen & Ritter, 2016; Lucheroni et al., 2019; Jafarian-Namin et al., 2019; Croonenbroeck & Stadtmann, 2019). However, we identified that the ARIMA model and its seasonal version were able to predict accurate values, especially at the beginning of the COVID-19 pandemic in Brazil, in which even the way of consuming electricity changed (Haiges et al., 2017; Mite-León & Barzola-Monteses, 2018; Carvalho et al., 2021).

This more stable behavior could be justified by government incentives and private investments in renewable area, such as PROINFA; in addition to the worldwide movement to make the energy matrix more sustainable (ANEEL, 2017; Aquila et al., 2017; Maciel et al., 2018; Medina, 2020). Yet, much more government efforts are needed to expand renewable generation in the country, as well as to maintain the electrical system stability, either by hybrid generation or by energy storage devices (Noronha et al., 2019; Reichert & Souza, 2021).

5 Conclusions

Renewable sources are responsible for more than half of all electricity generated in Brazil and, due to their relevance, the ARIMA models were applied to predict electricity generated from biomass, hydropower and wind sources, in the interval between January and June 2020, which corresponds to the first months of the COVID-19 pandemic in Brazil.

Despite the pandemic and the change in energy consumption behavior, the seasonal ARIMA model was able to predict electricity generation from renewable sources. Knowing that the main renewable sources of Brazilian electric matrix have seasonal behavior will help in planning the national electrical system.

The restriction of this study was that only renewable sources were analyzed, instead of all electric matrix sources. An important limitation of the study was the outdated database.

We suggest, for future research, to predict electricity generation from all sources that make up Brazilian electric matrix to evaluate interactions among variables and the volatility generated by the transition from non-renewable to renewable sources.

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Declaration of interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The variable of interest, amounts of electricity generated (GWh) from renewable sources, were collected at National Electric Energy Agency (ANEEL) open database: http://www.aneel.gov.br/dados/geracao.

References

Agência Nacional de Energia Elétrica – ANEEL. (2017). *Programa de incentivo às fontes alternativas.* Retrieved in 2021, July 7, from https://www.aneel.gov.br/proinfa

Agência Nacional de Energia Elétrica – ANEEL. (2020). *Geração por fonte.* Retrieved in 2021, July 1, from http://www.aneel.gov.br/dados/geracao

Akaike, H. (1974). A new look at the statistical model identification. *IEEE Transactions on Automatic Control*, 19(6), 716-723. http://dx.doi.org/10.1109/TAC.1974.1100705.

Alsharif, M. H., Younes, M. K., & Kim, J. (2019). Time series ARIMA model for prediction of daily and monthly average global solar radiation: the case study of Seoul, South Korea. *Symmetry*, 11(2), 240. http://dx.doi.org/10.3390/sym11020240.

Aquila, G., Pamplona, E. O., Queiroz, A. R., Rotela, P., Jr., & Fonseca, M. N. (2017). An overview of incentive policies for the expansion of renewable energy generation in electricity power systems and the Brazilian experience. *Renewable & Sustainable Energy Reviews*, 70, 1090-1098. http://dx.doi.org/10.1016/j.rser.2016.12.013.

Bakhtiar, A., Aslani, A., & Hosseini, S. M. (2020). Challenges of diffusion and commercialization of bioenergy in developing countries. *Renewable Energy*, 145, 1780-1798. http://dx.doi.org/10.1016/j.renene.2019.06.126.

Baruque, B., Porras, S., Jove, E., & Calvo-Rolle, J. L. (2019). Geothermal heat exchanger energy prediction based on time series and monitoring sensors optimization. *Energy*, 171, 49-60. http://dx.doi.org/10.1016/j.energy.2018.12.207.

Bhutto, A. W., Bazmi, A. A., Khadija, Q., Harijan, K., Karim, S., & Ahmad, M. S. (2017). Forecasting the consumption of gasoline in transport sector in Pakistan based on ARIMA model. *Environmental Progress & Sustainable Energy*, 36(5), 1490-1497. http://dx.doi.org/10.1002/ep.12593.

Box, G. E. P., & Jenkins, G. M. (1970). *Time series analysis, forecasting and control*. San Francisco: Holden Day.

Box, G. E., Jenkins, G. M., & Reinsel, G. C. (1994). *Time series analysis: forecasting and control* (3rd ed.). New Jersey: Prentice Hall.

Carvalho, M., Delgado, D. B. M., Lima, K. M., Cencela, M. C., Siqueira, C. A., & Souza, D. L. B. (2021). Effects of the COVID-19 pandemic on the Brazilian electricity consumption patterns. *International Journal of Energy Research*, 45(2), 3358-3364. http://dx.doi.org/10.1002/er.5877.

Čepin, M. (2019). Evaluation of the power system reliability if a nuclear power plant is replaced with wind power plants. *Reliability Engineering & System Safety*, 185, 455-464. http://dx.doi.org/10.1016/j.ress.2019.01.010.

Cotia, B. P., Borges, C. L. T., & Diniz, A. L. (2019). Optimization of wind power generation to minimize operation costs in the daily scheduling of hydrothermal systems. *International Journal of Electrical Power & Energy Systems*, 113, 539-548. http://dx.doi.org/10.1016/j.ijepes.2019.05.071.

Croonenbroeck, C., & Stadtmann, G. (2019). Renewable generation forecast studies – Review and good practice guidance. *Renewable & Sustainable Energy Reviews*, 108, 312-322. http://dx.doi.org/10.1016/j.rser.2019.03.029.

Daioglou, V., Doelman, J. C., Wicke, B., Faaij, A., & van Vuuren, D. P. (2019). Integrated assessment of biomass supply and demand in climate change mitigation scenarios. *Global Environmental Change*, 54, 88-101. http://dx.doi.org/10.1016/j.gloenvcha.2018.11.012.

Dickey, D. A., & Fuller, W. A. (1981). Likelihood ratio statistics for autoregressive time series with a unit root. *Econometrica*, 49(4), 1057-1072. http://dx.doi.org/10.2307/1912517.

Empresa de Pesquisa Energética – EPE. (2018). *Brazilian energy balance 2018 year 2017*. Rio de Janeiro: EPE.

Ferreira, J. H. I., Camacho, J. R., Malagoli, J. A., & Guimarães, S. C., Jr. (2016). Assessment of the potential of small hydropower development in Brazil. *Renewable & Sustainable Energy Reviews*, 56, 380-387. http://dx.doi.org/10.1016/j.rser.2015.11.035.

Ferreira, L. R. A., Otto, R. B., Silva, F. P., Souza, S. N. M., Souza, S. S., & Ando, O. H., Jr. (2018). Review of the energy potential of the residual biomass for the distributed generation in Brazil. *Renewable & Sustainable Energy Reviews*, 94, 440-455. http://dx.doi.org/10.1016/j.rser.2018.06.034.

Galvão, J., & Bermann, C. (2015). Crise hídrica e energia: conflitos no uso múltiplo das águas. *Estudos Avançados*, 29(84), 43-68. http://dx.doi.org/10.1590/S0103-40142015000200004.

González-Aparicio, I., & Zucker, A. (2015). Impact of wind power uncertainty forecasting on the market integration of wind energy in Spain. *Applied Energy*, 159, 334-349. http://dx.doi.org/10.1016/j.apenergy.2015.08.104.

Haiges, R., Wang, Y. D., Ghoshray, A., & Roskilly, A. P. (2017). Forecasting electricity generation capacity in malaysia: an auto regressive integrated moving average approach. *Energy Procedia*, 105, 3471-3478. http://dx.doi.org/10.1016/j.egypro.2017.03.795.

Hosseini, S. M., Saifoddin, A., Shirmohammadi, R., & Aslani, A. (2019). Forecasting of CO2 emissions in Iran based on time series and regression analysis. *Energy Reports*, 5, 619-631. http://dx.doi.org/10.1016/j.egyr.2019.05.004.

International Energy Agency – IEA. (2017). *Atlas of energy: share of renewables in total energy production (%).* Retrieved in 2019, November 28, from http://energyatlas.iea.org/#!/tellmap/-1076250891/1

Jadhav, V., Reddy, B. V. C., & Gaddi, G. M. (2017). Application of ARIMA model for forecasting agricultural prices. *Journal of Agricultural Science and Technology*, 19(4), 981-992.

Jafarian-Namin, S., Goli, A., Qolipour, M., Mostafaeipour, A., & Golmohammadi, A. M. (2019). Forecasting the wind power generation using Box-Jenkins and hybrid artificial intelligence: a case study. *International Journal of Energy Sector Management*, 13(4), 1038-1062. http://dx.doi.org/10.1108/IJESM-06-2018-0002.

Khair, U., Fahmi, H., Al-Hakim, S., & Rahim, R. (2017). Forecasting error calculation with mean absolute deviation and mean absolute percentage error. *Journal of Physics: Conference Series*, 930, 012002. http://dx.doi.org/10.1088/1742-6596/930/1/012002.

Kim, H., Kim, S., Shin, H., & Heo, J. H. (2017). Appropriate model selection methods for nonstationary generalized extreme value models. *Journal of Hydrology (Amsterdam)*, 547, 557-574. http://dx.doi.org/10.1016/j.jhydrol.2017.02.005.

Kuang, Y., Zhang, Y., Zhou, B., Li, C., Cao, Y., Li, L., & Zeng, L. (2016). A review of renewable energy utilization in islands. *Renewable & Sustainable Energy Reviews*, 59, 504-513. http://dx.doi.org/10.1016/j.rser.2016.01.014.

Kwiatkowski, D., Phillips, P. C. B., Schmidt, P., & Shin, Y. (1992). Testing the null hypothesis of stationarity against the alternative of a unit root. *Journal of Econometrics*, 54(1-3), 159-178. http://dx.doi.org/10.1016/0304-4076(92)90104-Y.

Lucena, A. F. P., Hejazi, M., Vasquez-Arroyo, E., Turner, S., Köberle, A. C., Daenzer, K., Rochedo, P. R. R., Kober, T., Cai, Y., Beach, R. H., Gernaat, D., van Vuuren, D. P., & van der Zwaan, B. (2018). Interactions between climate change mitigation and adaptation: the case of hydropower in Brazil. *Energy*, 164, 1161-1177. http://dx.doi.org/10.1016/j.energy.2018.09.005.

Lucheroni, C., Boland, J., & Ragno, C. (2019). Scenario generation and probabilistic forecasting analysis of spatio-temporal wind speed series with multivariate autoregressive volatility models. *Applied Energy*, 239, 1226-1241. http://dx.doi.org/10.1016/j.apenergy.2019.02.015.

Maciel, P. N., Fo., Alcócer, J. C. A., Pinto, O. R. O., & Dolibaina, L. I. L. (2018). Sustainable energy public policies planning: encouraging the production and use of renewable energies. *Revista Eletrônica em Gestão Educação e Tecnologia Ambiental*, 22, 10. http://dx.doi.org/10.5902/2236117034211.

Medina, V. (2020). *Incentivos fiscais na produção de energias renováveis.* Moore.Retrieved in 2021, July 7, from https://www.moorebrasil.com.br/blog/incentivos-fiscais-na-producao-de-energias-renovaveis/

Mite-León, M., & Barzola-Monteses, J. (2018). Statistical model for the forecast of hydropower production in Ecuador. *International Journal of Renewable Energy Research*, 8(2), 1130-1137.

Morettin, P. A. (2016). *Econometria financeira: um curso em séries temporais financeira* (3ª ed.). São Paulo: Blucher.

Noronha, M. O., Zanini, R. R., & Souza, A. M. (2019). The impact of electric generation capacity by renewable and non-renewable energy in Brazilian economic growth. *Environmental Science and Pollution Research International*, 26(32), 33236-33259. http://dx.doi.org/10.1007/s11356-019-06241-4. PMid:31515770.

Olatunji, O., Akinlabi, S., Madushele, N., & Adedeji, P. A. (2019a). Estimation of Municipal Solid Waste (MSW) combustion enthalpy for energy recovery. *EAI Endorsed Transactions on Energy Web*, 6(23), 159119. http://dx.doi.org/10.4108/eai.11-6-2019.159119.

Olatunji, O., Akinlabi, S., Madushele, N., & Adedeji, P. A. (2019b). Estimation of the elemental composition of biomass using hybrid adaptive neuro-fuzzy inference system. *BioEnergy Research*, 12(3), 642-652. http://dx.doi.org/10.1007/s12155-019-10009-6.

Pes, M. P., Pereira, E. B., Marengo, J. A., Martins, F. R., Heinemann, D., & Schmidt, M. (2017). Climate trends on the extreme winds in Brazil. *Renewable Energy*, 109, 110-120. http://dx.doi.org/10.1016/j.renene.2016.12.101.

Qarnain, S. S., Sattanathan, M., Sankaranarayanan, B., & Ali, S. M. (2020). Analyzing energy consumption factors during coronavirus (COVID-19) pandemic outbreak: a case study of residential society. *Energy Sources. Part A, Recovery, Utilization, and Environmental Effects*, 1-20. http://dx.doi.org/10.1080/15567036.2020.1859651.

Ramser, C. A. S., Souza, A. M., Souza, F. M., Veiga, C. P., & Silva, W. V. (2019). The importance of principal components in studying mineral prices using vector autoregressive models: evidence from the Brazilian economy. *Resources Policy*, 62, 9-21. http://dx.doi.org/10.1016/j.resourpol.2019.03.001.

Razmjoo, A., Shirmohammadi, R., Davarpanah, A., Pourfayaz, F., & Aslani, A. (2019). Stand-alone hybrid energy systems for remote area power generation. *Energy Reports*, 5, 231-241. http://dx.doi.org/10.1016/j.egyr.2019.01.010.

Reichert, B., & Souza, A. M. (2020). Previsão e interação dos preços da celulose brasileira nos mercados interno e externo. *Ciência Florestal*, 30(2), 501-515. http://dx.doi.org/10.5902/1980509838223.

Reichert, B., & Souza, A. M. (2021). Interrelationship simulations among Brazilian electric matrix sources. *Electric Power Systems Research*, 193, 107019. http://dx.doi.org/10.1016/j.epsr.2020.107019.

Renn, O., & Marshall, J. P. (2016). Coal, nuclear and renewable energy policies in Germany: from the 1950s to the “Energiewende”. *Energy Policy*, 99, 224-232. http://dx.doi.org/10.1016/j.enpol.2016.05.004.

Saheli, M. A., Fazelpour, F., Soltani, N., & Rosen, M. A. (2019). Performance analysis of a photovoltaic/wind/diesel hybrid power generation system for domestic utilization in winnipeg, manitoba, Canada. *Environmental Progress & Sustainable Energy*, 38(2), 548-562. http://dx.doi.org/10.1002/ep.12939.

Salles, A. A., & Campanati, A. B. M. (2019). The relevance of crude oil prices on natural gas pricing expectations: a dynamic model based empirical study. *International Journal of Energy Economics and Policy*, 9(5), 322-330. http://dx.doi.org/10.32479/ijeep.7755.

Senna, V., & Souza, A. M. (2016). Assessment of the relationship of government spending on social assistance programs with Brazilian macroeconomic variables. *Physica A*, 462, 21-30. http://dx.doi.org/10.1016/j.physa.2016.05.022.

Shen, Z., & Ritter, M. (2016). Forecasting volatility of wind power production. *Applied Energy*, 176, 295-308. http://dx.doi.org/10.1016/j.apenergy.2016.05.071.

Silva, A. R., Pimenta, F. M., Assireu, A. T., & Spyrides, M. H. C. (2016). Complementarity of Brazil's hydro and offshore wind power. *Renewable & Sustainable Energy Reviews*, 56, 413-427. http://dx.doi.org/10.1016/j.rser.2015.11.045.

Souza, F. M. (2016). *Modelos de previsão: aplicações à energia elétrica ARIMA-ARCH-AI e ACP* (1ª ed.). Curitiba: Appris.

Uddin, M. N., Taweekun, J., Techato, K., Rahman, M. A., Mofijur, M., & Rasul, M. G. (2019). Sustainable biomass as an alternative energy source: bangladesh perspective. *Energy Procedia*, 160, 648-654. http://dx.doi.org/10.1016/j.egypro.2019.02.217.