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Modeling of Brazilian Wind Power Generation Capacity: A Multivariate Analysis with Neural Networks

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Abstract— Over the last twenty years, Brazil has experienced significant changes in its electric energy matrix, notably with the expansion of wind and solar energy sources. In the early 2000s, hydroelectric plants with a capacity of 70 gigawatts (GW) were responsible for generating 90% of the country's electricity, while solar and wind sources contributed merely 1%. Today, the scenario has evolved, with wind and solar energy comprising approximately 25% of the national generation, indicating a departure from the previous hydro-dominated matrix. This research aims to apply specific types of neural networks to multivariate data to forecast Brazil's wind power generation capacity, providing insight into the potential for future energy strategies. This research contributes as a as a decision support tool contemplating relevant information for analysts, researchers, and participants in the renewable energy market. The monetary volume destined to import key components of the wind, considering specific time lags, was utilized to forecast the Installed capacity of the wind farms in Brazil. The Toda-Yamamoto Causality Tests revealed unidirectional Granger causality in the sense of the Import variable for the Brazilian Installed Capacity variable for wind energy production. Another result obtained was the finding that the variable that matters most in the multivariate configuration of the Neural Network is the variation in Installed Capacity in megawatts, followed by the import volume of wind energy components, which exhibited critical lags at 3 and 6 months.

Keywords— *Renewable Energy; Wind-Solar Growth; Neural Network Forecasting.*

1. Introduction

Brazil experienced a significant energy crisis referred to as "the Blackout of 2001," which was the most significant energy crisis at the time of its occurrence. The warning signs began with an increase in energy imports in 2000, and the mentioned blackout lasted almost a year, significantly impacting Brazilian society [1]. The crisis led to drastic changes in energy generation and supply, resulting in a nationwide power shortage. The scenario had environmental, economic, and structural causes. The 2001 blackout is often attributed to insufficient of rainfall and inadequate investment in energy production and distribution. Before the crisis, experts had already warned of an impending energy crisis and the risk of an energy shortfall greater than 5%, noting the significant discrepancy between supply and demand. Analysts maintained that problems were imminent, citing a lack of investment in new power plants and energy transmission lines and pointing to delays in ongoing energy projects. The situation became critical due to climate-related changes, notably the significant reduction in rainfall [2]. In July 2001, the Brazilian government formed a commission, led by Jerson Kelman — the then-president of the National Water Agency (ANA) and subsequent general director of the National Electric Energy Agency (ANEEL) — to investigate the causes of the energy rationing. The commission's report implicated several entities, including the Ministry of Mines and Energy, ANEEL, and the National System Operator (ONS). In response to the energy crisis of 2001, the Emergency Wind Energy Program (Proeólica) was created to encourage wind energy generation. This was done through Provisional Measure 2.198-3 of June 2001. As a result of this measure, the Government Council created the Electric Energy Crisis Management Chamber, which established standards for programs to address the energy crisis and implemented further measures [3].

Since the 2001 water crisis, Brazil has faced ongoing threats of energy rationing, exacerbated by climate change's impact on hydrology, which powered 65.2% of its electricity in 2020. The Brazilian Geological Service – CPRM noted a severe water crisis 2021, with significant declines in hydrographic basin flows across the South, Southeast, and Midwest. This, coupled with the La Niña phenomenon affecting rain distribution, especially in energy-critical regions, led to an energy crisis akin to 2001. Factors such as climate change, global warming, deforestation, and reliance on a hydroelectric-dominant energy matrix without alternative plans contribute to these crises. As of October 2022, Brazil's largest hydroelectric plants include Belo Monte in Pará with 11,233,100.00 kW, Tucuruí, also in Pará, with 8,535,000.00 kW, and the binational Itaipu plant in Paraná with 7,000,000 kW on the Brazilian side, highlighting the country's vulnerability to hydrological variability and climate impacts.

Brazil has shown a change in its electric energy matrix over the last twenty years, with the expansion of wind and solar energy sources. hydroelectric plants, with a capacity of 70 gigawatts (GW), accounted for 90% of the nation's electricity generation, with solar and wind contributing a mere 1%. Currently, wind energies add up to 26 GW of power, corresponding to 13% of the country's electricity. Solar energy totals 30 GW of capacity, with 21 GW in Distributed Generation (GD) solar, approximately 12% of national generation [4]. Moreover, global investment in clean energy generation technologies is expected to reach $1.7 trillion by 2023, surpassing fossil fuels (gas, oil, and coal) by just over $1 trillion for the eighth consecutive year. Suppose the pace of annual investments is maintained. In that case, the total by 2030 will exceed the level needed to meet the commitments of the Paris Agreement and prevent the average global temperature increase to below 1.5 degrees Celsius. The World Energy Investment 2023 report, released in May by the International Energy Agency (IEA), disclosed these data. This research aimed to apply neural networks with multivariate data to predict the capacity of Brazilian wind energy generation, thereby contributing as a decision-support tool and providing relevant information for analysts, researchers, and participants in the renewable energy market.

2. Wind Farm in Brazil

Wind energy has served various mechanical energy needs, such as pumping water and milling grain, for many years. The initial efforts to generate electricity from wind date back to the late 19th century. However, it was only after the international oil crisis of the 1970s that increased interest and investment spurred the development and commercialization of wind power technology (Brazilian Institute of Information in Science and Technology, 2022).

Wind energy usage began in Europe, now holding a large share of the world's installed capacity [3]. This region has been a focal point for technological development initiatives, particularly in Germany and Spain, which are home to major wind turbine manufacturers. China, the United States, and India have also ramped up their wind installations in recent years, achieving 75.6 GW, 60.0 GW, and 18.4 GW, respectively [5]. Despite Brazil's modest presence in the global wind market, the country has made significant strides in its installed capacity over the past decade. Programs such as the Emergency Wind Energy Program (Proeólica), the Alternative Energy Sources Incentive Program (Proinfa), and energy auctions have been instrumental in enhancing the contribution of wind energy to Brazil's electricity matrix.

Diversification of energy sources and the rise of solar and wind energy have led to significant changes in Brazil's electric energy matrix over the past two decades. In the early 2000s, hydroelectric plants' electricity, with their 70 gigawatts (GW) of capacity, generated 90% of the country's, while solar and wind contributed a mere 1%. Today, wind energy contributes 26 GW, representing 13% of the country's electricity. Solar power adds up to 30 GW of capacity, with 21 GW in Distributed Generation (GD) solar, comprising approximately 12% of national generation [4]. Wind and solar energy growth in the Brazilian matrix largely stems from decreased technology costs. The International Renewable Energy Agency [6] emphasizes that the cost of adopting solar and wind energy has dropped by 80% over the past decade. These sources are highly competitive in Brazil due to strong sunlight and winds. The trade winds, for instance, boost wind energy competitiveness in the Northeast to over 50%, which is more than twice the global average. From 2010 to 2021, renewable energies have seen a seismic shift in competitiveness. The international average levelized cost of electricity (LCOE) for newly commissioned utility-scale solar photovoltaic projects plummeted by 88% between 2010 and 2021, while onshore wind dropped by 68%, CSP by 68%, and offshore wind by 60%. The IRENA cost analysis program, initiated in 2012, consistently reports cost and performance data for renewable energy technologies based on a database with information on around 21,000 renewable energy projects globally.

The shift in Brazil's energy matrix began in 1992 when the Brazilian Wind Energy Center (CBEE) and the Pernambuco Energy Company (Celpe) partnered with a Danish institute to install a wind turbine in Fernando de Nogueira [3]. That year also saw the start of pilot projects in Taíba in São Gonçalo do Amarante and Mucuripe in Ceará, with anemometer installations. The Annual Wind Energy Generation Bulletin released by ABEEólica in 2020 reported 686 wind parks and an installed wind energy capacity of 17.75 GW, marking a 14.89% increase from December 2019's 15.45 GW capacity. The industry constructed 66 new wind parks in 2020, adding 2.30 GW in new capacity. The pandemic posed significant challenges to the industry, including the absence of auctions due to decreased demand and the halting of regulated market sales in 2020. By the end of 2021, wind energy boasted 795 plants and an installed capacity of 21.57 GW, reflecting a 21.53% growth in power from December 2020's 17.75 GW. That year witnessed the establishment of 110 new wind parks and the revocation of one, adding up to 3.83 GW of new capacity, a record for Brazil's wind installations. Brazil ranked third globally for new wind energy installations, based on data from the Global Wind Energy Council (GWEC) shared by ABEEólica in the 2021 report.

Over the past 11 years, Brazil has experienced exponential growth in wind energy generation. In 2021, data from the Statistical Review of World Energy revealed a 27% increase in generation from 2020 and a 3.22% increase since 2010. Brazil was the fourth-largest wind energy producer in terawatt-hours for that year, only behind China, the United States, and Germany.

3. Toda and Yamamoto Causality Test

To address some deficiencies found in other causality tests, such as the stationarity assumption, Toda and Yamamoto developed an alternative test in 1995 [7]. The Toda and Yamamoto procedure involves a modified Wald test (mwald) on the parameters of a vector autoregression (VAR) model. The test operates directly on the least squares estimators of an augmented VAR in levels. The authors assert that in integrated systems, the Wald test for linear constraints on the parameters of a VAR(z) follows a chi-squared (χ^2) asymptotic distribution. It does not depend on the stationarity of the system when one estimates a

VAR of $(z + e_{max})$, where (e_{max}) is the maximum order of integration of the series. One performs the Wald test for the non-causality hypothesis of Granger on the first z coefficients, disregarding the last (e_{max}) coefficients. These extra lags are indispensable to ensure the test statistic follows an asymptotically chi-squared (χ^2) distribution.

Thus, the non-causality test of Granger, modified and suggested by Toda and Yamamoto, consists of three main steps. (i) Step one is to determine the optimal number of lags (z) and the maximum integration order of the system (e_{max}). One can select the optimal number of lags using Schwarz's Information Criterion (SIC) or Akaike's Information Criterion (AIC), among others. As for the maximum integration order, one can determine it in two ways: (a) to avoid potential biases from pre-tests, simply set $(e_{max} = 1)$, assuming that macroeconomic variables are generally I(1); (b) or examine the univariate properties of the time series using the augmented Dickey-Fuller (ADF) test and/or the Phillips-Perron (PP) test. (ii) The second step involves estimating a VAR in levels with a total of $(z + e_{max})$ lags. The third and final step is to apply the Wald test on the first z coefficients to test the non-causality hypothesis of Granger. The hypotheses to be tested are:

The hypotheses to be tested are as follows:

$$\begin{cases} H_0: X \text{ does not cause } Y \\ H_1: X \text{ cause } Y \end{cases} \quad (1)$$

Given this, researchers will apply the Toda-Yamamoto causality test to ascertain the presence of causality.

It's important to highlight that the Toda-Yamamoto test considers the probability of committing two types of errors:
Type I error (α): Rejecting the null hypothesis (H_0) when it's true (concluding there's causality when there isn't).
Type II error (β): Failing to reject the null hypothesis (H_0) when it's false (concluding there's no causality when it exists).
The goal is to minimize the probability of both errors. The significance level (α) is pre-defined r and is typically set at 5% (0.05). The lower the α, the less likely you are to commit a type I error, but the more likely you are to commit a type II error. The Toda-Yamamoto test aims to provide robust results even without the need for stationary series, aiding in the decision about the existence of causality between variables.

4. Neural Networks in wind energy series modeling

Research concerning neural networks has progressed significantly in the 21st century. Human decision-making capabilities are programmed into networks to make decisions and predict outcomes through training, rendering them more assertive and efficient. The information processing paradigms known as neural networks are premised on the biological neural systems of humans. [8] Introduce a forecasting methodology for energy from weather data refined with artificial neural networks. The authors conclude that the average forecast values for wind speed and power have a good approximation with actual values, demonstrating the suitability of the neural network method for wind forecasting. However, considerable work remains to be done to reduce uncertainties and enhance the reliability of wind generation in Brazil.

Bibliometrics was used to identify the volume of publications on wind energy and neural networks. According to [9], describe the bibliometric method consists of an interdisciplinary scientific approach to quantifying the academic output of individuals and institutions regarding a specific topic. Qualitative insights are then drawn from its graphical and statistical results. The sample of this study was extracted from the Scopus indexing base, enabling the compilation of studies associated with influential journals that provide, in turn, essential results for this research field [10]. Publications were obtained using the keywords ["wind energy" AND "neural networks"] so that they must appear in the title, abstract, or keywords of the articles.

Based on the specified criteria, 1,760 documents were found published from 1994 to June 2023. Among the publications are 980 articles, 641 conference papers, and 35 book chapters. In 2012, 68 research papers were published, while in 2021, there were 204 works on the topic; in 2022, there were 307, and as of June 2023, 137 studies have been documented. This trend demonstrates the exponential growth of research on wind energy and neural networks.

In terms of geographic distribution, China leads in publishing, contributing 22.8% of the compiled documents, followed by India (18.5%) and the United States (7.5%). The participation of other countries in the literature adds up to 51.2%, indicating a concentration of publications in the first three countries mentioned. The authors who published the most works related to the topic were: Wang, Jianzhou, with 16 documents and cited by over 8,300 articles. The second most relevant author was Zhang Yagang, who has 15 documents and has been cited in more than 1,300 research papers. In third place is the researcher Petkovič, Dalibor, with 13 articles covering the topic and more than 4,230 citations. Regarding the most cited articles, the first place went to the paper titled: A Microgrid Energy Management System Based on the Rolling Horizon Strategy. Published in 2013 by the authors Palma-Behnke, R., Benavides, C., Lanas, F., Severino, B., Reyes, L., Llanos, J., & Sáez (cited by 604 other research papers). The second most noted work was on comparing three artificial neural networks for wind speed forecasting, published by [11] Li, G., & Shi, J. in 2010 (cited by 594 other research papers). In third place is the article named: Optimal Energy Storage Sizing and Control for Wind Power Applications, published in 2011 by researchers 23 Brekken, T. K., Yokochi, A., Von Jouanne, A., Yen, Z. Z., Hapke, H. M., & Halamay (cited by 440 other research papers).

[12] Introduced a novel energy management system (EMS) based on a rolling horizon (RH) strategy for a renewable microgrid. The EMS delivers online setpoints for each generation unit and signals to consumers based on a demand-side management (DSM) mechanism. The proposed SGA - Environmental Management System was deployed for a microgrid composed of photovoltaic panels, two wind turbines, a diesel generator, and an energy storage system. The authors devised a coherent forecasting information scheme and an economic comparison framework between RH and the standard unit commitment (UC). The solar and wind energy forecasts were based on phenomenological models enriched with current data. Addionatlly, they suggested a neural network for predicting electrical consumption two days ahead. The system described by the authors underwent validation using real datasets from an existing microgrid in Chile (ESUSCON).

[13] presented sizing and control methodologies for a zinc-bromine flow battery-based energy storage system. The results show that the power flow control strategy markedly influences the proper sizing of the system's nominal power and energy. In particular, artificial neural network control strategies resulted in

significantly lower-cost energy storage systems than simplified controllers. The findings by the authors demonstrated that through more effective control and coordination of energy storage systems, the predictability of wind plant outputs can be improved, and the associated integration cost due to reserve requirements can be diminished.

5. Architecture and Topology of The Artificial Neural Network used to Predict Installed Capacity in Megawatts (Mw)

The term "neural network topology" refers to the way neurons are arranged within the network and its structure. The type of learning algorithm used is directly related to the network's topology. In the present paper, recurrent networks were selected, where feedback occurs when the output of a neuron is applied as input to the same neuron or other neurons in previous layers, establishing a cycle within the graph. In this configuration, the outputs are fed back as input signals to other neurons, thus being employed for the processing of time-variant systems. The architecture in question is commonly used in time series forecasting, optimization, system identification, and process control.

The capability of a neural network to learn from its environment and enhance its performance through learning is its main feature. This learning is the process by which the internal representation of the system improves in response to an external stimulus, making it capable of achieving a specific goal [14]. The learning was carried out through Error Correction. This is used in supervised training, and in it, the synaptic weights are adjusted through the error, which is obtained by the discrepancy between the network's output value and the expected value in a training cycle.

In the present article, Multilayer Perceptron Networks were addopted. According to [15], the Multilayer Perceptron is the most widely used model in neural network applications using the backpropagation training algorithm. A Multilayer Perceptron is a variant of the original Perceptron model proposed by Rosenblatt in the 1950s. The network has one or more hidden layers between its input and output layers; the neurons are organized in layers, connections are always directed from the lower to the upper layers, and neurons in the same layer are not interconnected [15].

The number of hidden layers in a Multilayer Perceptron and the number of nodes in each layer can vary for a given problem. In general, according to [16]), more nodes offer greater sensitivity to the problem being solved, but also the risk of overfitting. According to the author, offen, a single hidden layer network with $2n + 1$ neurons, where n is the number of inputs, may be recommended, but this is based on empirical evidence more than anything else. [16] noted that as the number of neurons within the hidden layer increases, the error coverage of the result approaches zero. Even at the stage where 40 neurons are used, the network will be able to produce optimal results. According to [16], there are many 'rule of thumb' methods for determining the correct number of neurons to use in the hidden layers, such as: (i) The number of hidden neurons should be between the size of the input layer and the size of the output layer. (ii) The number of hidden neurons should be 2/3 the size of the input layer, plus the size of the output layer, and (iii) The quantity of hidden neurons ought to be fewer than double the dimension of the input layer. For the authors, these three rules offer an initial framework to be taken into account. Ultimately, the selection of the architecture for the neural network will come down to trial and error.

According to [17], Multilayer Perceptron Networks are defined by: (i) Their configuration or architecture - the number of layers, the number of neurons per layer, etc., are determined. (ii) Activation methods - the transfer functions used in various neurons are specified. (iii) The specification of the gradient descent learning method using the generalized delta rule, conjugate gradient, or another method is provided. (iv) Event specification - it is determined whether the weight update is performed 'online' (i.e., after each training pattern) or 'offline' (at the end of each epoch, after all training patterns have been presented).

The algorithm applied followed the subsequent steps: Stage 1: Network initialization was carried out with weights being initialized randomly. Stage 2: Feedforward was conducted, where information was transmitted from the input layer through the hidden layer(s) and subsequently to the output layer via the sigmoid activation function. Stage 3: Error evaluation was performed to determine if (i) the error was sufficiently small to satisfy the requirements or (ii) the number of iterations had reached a pre-determined limit. Step 4: Backpropagation was used where the error in the output layer was utilized to modify the weights. The algorithm backpropagated the error through the network and calculated the gradient of the change in error relative to the changes in the weights' values. Stage 5: Adjustments were made where the weights were adjusted using the change gradients to reduce the error. The weights and biases of each neuron were adjusted by a factor based on the derivative of the activation function.

In the current study, several variants of neural networks were tested, incorporating changes in Installed Capacity in megawatts (MW) from the previous period and variations in the monetary volume allocated for importing key components of wind farms at different lags (1, 2, 3, 4, 5, 6, 7, and 8 lags). Both single-layer and two-layer networks were tested, with hidden layer neuron counts varying as follows: 1.2, 3, 4, 5, 6, 7, and 8. Activation functions such as logistic and Tanh were implemented. The evaluation of models included calculating the Sum of Squared Errors (SSE) using the following equation:

$$SSE = \sum_{i=1}^{n} \left(Y_i - \widehat{Y_i}\right)^2 \qquad (2)$$

where Y_i represents the actual observed value and $\widehat{Y_i}$ represents the predicted value by the neural network model.
The algorithm utilized for training the neural networks was rprop+ (Resilient Backpropagation with Weight Backtracking). rprop+ is a variant of the backpropagation algorithm that adapts the learning rate individually for each weight based on the sign of the gradient and the previous update direction. This allows for faster convergence and improved training efficiency.
Learning rates in the rprop+ algorithm were constrained to the range of 0.6 to 1.2. The Neuralnet and NeuralNetTools packages were used for this study. It's important to note that the dataset, comprising 140 data points per series, was divided into training (128 data points) and network validation (12 data points) sets.

Additional neural network variants were also tested, involving only changes in Installed Capacity in megawatts (MW) from the previous period as input for predicting fluctuations in Installed Capacity in megawatts (MW) at time t. Again, networks with one and two hidden layers were tested, varying the neuron counts in the hidden layer as follows: 1.2, 3, 4, 5, 6, 7, and 8.

After completing tests with multivariate and univariate data, two formulations were compared: multivariate and univariate. The following equations were used:

$$net_{1t} = w_0 + w_1(Cap_{t-1}) + w_2(Imp_{t-1}) + w_3(Imp_{t-3}) + w_4(Imp_{t-6})$$

$$net_{2t} = w_0 + w_1(Cap_{t-1})^2 \quad (3)$$

In net_{1t}, the additional variable is the variation in the monetary volume allocated for importing key components of wind farms (Wind turbines, Wind blades, and Wind towers) at lags one, three, and six. Equation net_{2t} only considers the series of Installed Capacity variation in megawatts (MW) at time t with a lag of one.

When forecasting historical values using artificial neural networks (ANNs), actual values can be compared with estimated values to determine the level of forecast error generated by the model. Various metrics were used; in this study, MAD (Mean Absolute Deviation), MAPE (Mean Absolute Percentage Error), and RMSE (Root Mean Square Error) were employed.

6. Results

In this section, analyses and results of the current study are detailed. The evaluation commenced to forecast the installed capacity of wind farms in Brazil, through the import of key components necessary for their implementation as the explanatory variable, such as: Turbine, Towers, and Wind blades, data on imports (US$) and installed capacity (MW) were collected monthly from January 2010 to December 2022.

The import records were collected from the Contrade data system, and the 6-digit S.H. (Harmonized System) codes applied were 850231, 730820, 841290, and 850232. The codes include: (i) Wind turbines: Wind turbines with power exceeding 750 KW and wind turbines with power not exceeding 750 KW. (ii) Wind towers: Wind towers and their sections, of iron or steel, and (iii) Wind blades: Parts of wind turbines, including wind blades. Figure 1 presents the monthly values and the cumulative values for the period analyzed.

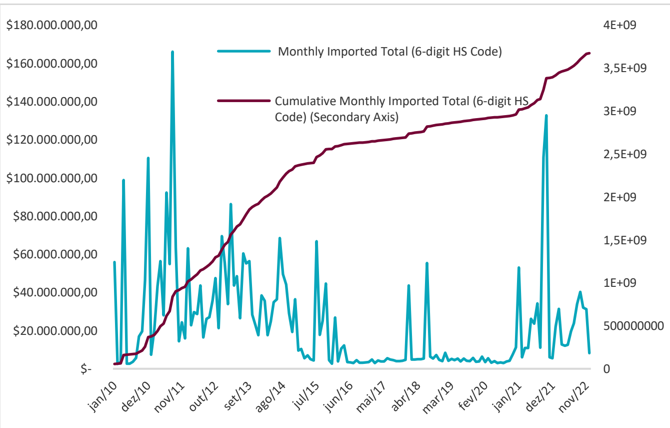

Fig. 1. Imports of components for wind energy production from 2010 to 2022, monthly data

Source: Own elaboration based on the analyzed data.

A notable rise in funds allocated to components for the expansion and modernization of Brazilian wind farms is observed. Intervals of substantial investment were recorded, particularly in the last two quarters of 2021 (US$ 300,405,877) and in the final two quarters of 2011 (US$ 202,581,391). From 2015 to 2020, imports were less elevated with a monthly average of US$ 8,408,140. It is pertinent to note that the capital goods referred to here have a minimum lifespan of 20 years (turbines and towers), while wind blades are expected to last 30 years.

To analyze the main traits of the observed series, it is essential to underscore the descriptive statistics. The use of these statistical measures is crucial for facilitating the examination of diverse datasets; they serve to condense an extensive array of values from the same source, allowing for a general overview of the variable of interest. In Table 1, the key metrics of the import and installed capacity series can be assessed. It is noted that the maximum invested in imports was an approximate value of 166,033,993.00 dollars, occurring in August 2011, while the nadir was in February 2010, with approximately 2,561,870.00 dollars invested. Another important point is that over the span of 12 full years, the average value committed to the importation of essential parts for the implementation of wind farms was 23,540,177.00 dollars. Regarding skewness, it can be said that the positive sign indicates that the distribution is right-skewed, and as 2.19 is greater than the reference range [-1, 1], it is seen that the data presents a high degree of skewness. Addionally, the Import series (US$) exhibits kurtosis of 9.21, surpassing the normative value of 3, which indicates that the curve is leptokurtic, i.e., it is less flat than the normal curve. Therefore, the distribution's peak is more pronounced, meaning that the data are more concentrated.

As for the measures of the centrality of the Installed Capacity series (MW), it is noted that the average monthly installed capacity is approximately 9,182 (MW). Regarding the skewness, the value of 0.30 is positive and is within the reference range [-1, 1], resulting in a positive skewness, and the data are more symmetrical. The kurtosis presented a value of 1.81, below the reference value of 3, indicating the existence of a platykurtic curve; this behavior points to the existence of light or thin tails with low peaks.

TABLE I. METRICS OF THE OBSERVED SERIES

METRICS	IMPORT (US$)	INSTALLED CAPACITY (MW)
Minimum	$2,561,870.00	638.60
Median	$11,692,508.00	9,214.40
Mean	$23,540,177.00	9,181.00
Maximum	$166,033,993.00	23,624.00
Standard Deviation	$27,217,005.00	6,986,749.00
Coefficient of Variation	1.16	0.76
Skewness	2.19	0.30
Kurtosis	9.21	1.81

Source: Own elaboration based on the analyzed data

The Installed Capacity data were collected from ANEEL - National Electric Energy Agency. The data are monthly, spanning from 2010 to 2022. The analyzed sample is grouped in megawatts (MW), totaling 156 observations. Figure 2 illustrates that the installed capacity shows a growth trend, reaching approximately 23,624 MW in 2022. It is observed that until 2014, the growth was exhibiting a steady behavior, and from this period onwards, the curve becomes steep, with very few periods of decline.

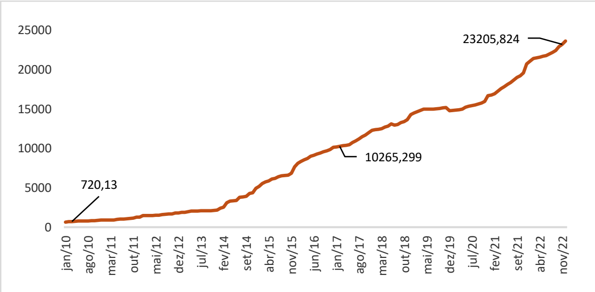

Fig. 2. Installed Capacity in Megawatts (MW) - Brazil from 2010 to 2022, monthly data.

Source: Own elaboration based on the analyzed data.

To verify the causality between the variables addressed in this study, the Granger causality test proposed by Toda and Yamamoto (1995) was applied. Vector autoregression (VAR) models were estimated with the variables of installed Capacity in MW and Importation of the most important components for the implementation of wind farms, both in logarithmic scale (ln). The Toda and Yamamoto test was applied considering an ($\alpha = 0.05$). In Table 2, it is possible to observe the result of the test; it is noted that with the p-value result of (0.85986), there is no evidence to reject (H_0), that is, the hypothesis of non-existence of causality from Installed Capacity to Importation was not rejected. However, the test applied considering that Importation does not cause Capacity rejected the null hypothesis ((H_0)) at a p-value of (0.00096). Thus, the tests showed unidirectional Granger causality from the Importation variable to the Capacity variable. Therefore, it can be concluded that the Importation of the main components for the implementation of wind farms causes the installed Capacity in MW.

TABLE 2 – TODA-YAMAMOTO CAUSALITY TEST

TESTS	**CHI-SQUARED STATISTIC χ^2**	**P-VALUE**
Installed Capacity does not Granger-cause Importation	2.576	0.85986
Importation does not Granger-cause Installed Capacity	22.548*	0.00096

Source: Own elaboration based on the analyzed data. Note: The asterisk (*) indicates that (H_0) – no causality, was rejected at the 5% significance level.

Figure 3 presents the configuration of the selected neural network with the best performance. As can be seen, the inputs (input) CapaIns1, Imp_acu1, Imp_acu3, and Imp_acu6 represent the variations of the selected series with lags (Installed Capacity in megawatts (MW) Brazil and Imports of components for wind energy production). The variable CapaIns (output) is the Installed Capacity in megawatts (MW) in Brazil predicted by the ANN (Artificial Neural Network).

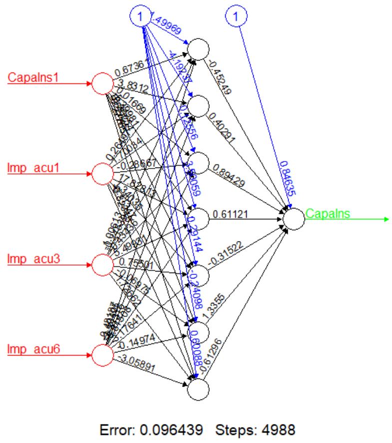

Fig. 3. Artificial Neural Network – Configuration (net_{1t}) (Equation 1)
Source: own elaboration

Figure 4 shows a bar graph with the relative importance of input variables in neural networks using Garson's algorithm. Garson's algorithm was originally described by [18] and later modified by [19]. The function employed, Garson is an implementation of the method described in [20], which identifies the relative importance of each variable as an absolute magnitude. For each input node, all weights connecting an input through the hidden layer to the response variable are identified to return a list of all the specific weights of each input variable. The aggregated products of the connections for each input node are then proportionally adjusted relative to all other inputs. A value for each input node indicates the relative importance as an absolute magnitude from zero to one. The method described in [24] (also referenced in [19]) ascertains the relative importance of explanatory variables for a single response variable in a supervised neural network by deconstructing the model's weights. The relative importance (or the strength of the association) of a specific explanatory variable to the response variable can be gauged by identifying all the weighted connections between the nodes of interest. All the weights connecting the specific input node passing through the hidden layer to the response variable are identified.

As illustrated in Figure 4 the most important variable in the net_{1t} configuration is the variation of Installed Capacity in megawatts, followed by the changes of Imports of components for wind energy production with a lag of 3, 1, and 6 months.

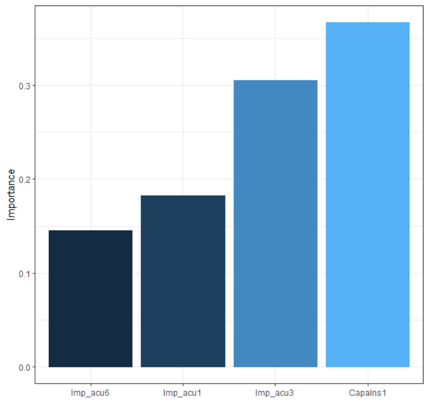

Fig. 4. Relative Importance of Input Variables in Neural Networks Using Garson's Algorithm
Source: own elaboration

Figure 5 displays a sensitivity analysis of the model's responses in a neural network for input variables using the Lek profile method. The Lek profile method [20] can be extended to any statistical R model with a prediction method. However, it is one of the few methods used to assess sensitivity in neural networks. The profile method can appraise the influence of explanatory variables by producing a plot of the predicted response across the spectrum of values for each variable. Initially, the profile method examined the impact of each variable while fixing the other explanatory variables at various quantiles. All explanatory variables are maintained at their average values, while the variable of interest is sequenced from its minimum to maximum value across the entire range of observations. This matrix (or data frame) is then used to predict the values of the response variable.

In Figure 5, the legend labeled 'Groups' indicates the colors corresponding to each group. The groups describe the values at which the unassessed explanatory variables were held constant. Each facet of the graph shows the bivariate relationship between a response variable and an explanatory variable. The multiple lines per graph indicate the change in relationship when the other explanatory variables are held constant.

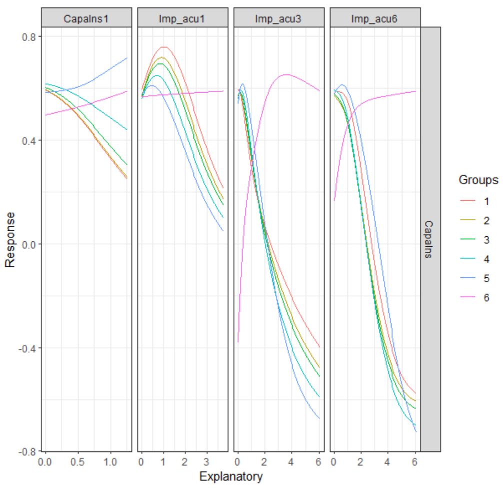

Fig. 5. Sensitivity Analysis Using Lek Profile Method, where in the analysis of each predictor variable the others were kept at their minimum values, 1st quartile, median, 3rd quartile, and maximums (Groups from 1 to 6, respectively).
Source: own elaboration

The Lek profile method elucidates the behavior of the model's output over the range of a specific input variable while all others are held fixed. The lekprofile function, used in this research, evaluates the impacts of input variables by generating a graph of model predictions across the range of values for each variable. In Figure 5, the number of lines equals the number of observations in the original dataset, and the number of columns equals the number of explanatory variables. Every explanatory variable is held steady (at the median), while the focal variable is sequenced from its minimum to its maximum. This matrix is subsequently applied to predict the values of the response variable. This procedure is replicated for each explanatory variable to obtain all the response curves.
The objective is to examine the system's response around its nominal point. The groups from 1 to 6 represent the minimum, 20th, 40th, 60th, 80th percentiles, and maximum, respectively. When the variables were fixed at the minimum value (group 1), the accumulated import variable over three months exerted the most influence (greater amplitude on the graph) on the installed capacity of wind farms. The monthly import variable exhibits the same pattern of influence across all groups except for group 1 (minimum). In groups 2 to 6, the accumulated import variables over three and six months significantly influence the installed capacity of wind farms. This fact can be observed by the steeper slope of the curves in the graphs (Figure 5).
As shown in Figure 6, the model with the multivariate formulation yields a more accurate approximation to the actual values. Table 3 lists the error values for each configuration, for both the training and validation parts of the neural network. The neural network containing the variation of Installed Capacity in megawatts (MW) in the previous period and the monetary volume variation allocated to importing main wind farm components at different lags (1, 3, and 6) registered lower error measures. Thus, it proved more efficient than the network that contained only the series of variations of Installed Capacity in megawatts (MW).

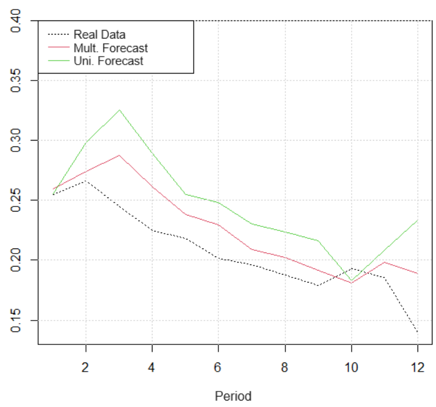

Fig. 6. Out-of-sample forecast of the variation of Installed Capacity in megawatts (MW) in Brazil using the two RNA arrangements compared in this research (see equation 1 and 2).
Source: own elaboration

TABLE 3 – ERROR MEASURES CALCULATED FOR EACH NETWORK CONFIGURATION.

TWORK CONFIGURATIONS	TRAINING ERROR MEASURES	VALIDATION ERROR MEASURES
	MAD	RMSE
Univariate (1 lag)	2.1%	0.40%
Multivariate (with variation of the US$ volume imported of selected products with lags 1,3 and 6)	1.9%	0.37%

Source: own elaboration

7. conclusion

In the last 20 years, Brazil diversified its energy matrix, increasing wind and solar energy contributions. Initially, hydroelectric plants generated 90% of electricity with 70 GW capacity, while sun and wind were nearly negligible at 1%. Now, wind energy contributes 26 GW (13%) and solar energy 30 GW, with 21 GW from distributed generation, totaling 12% of the country's electricity. Brazil is now the third-largest wind power developer globally, with a 21.53% growth in wind capacity from 2020 to 2021, reaching 21.57 GW from 795 plants and adding 3.83 GW with 110 new wind farms.

This study was conducted to scrutinize Brazil's energy matrix and the change in Installed Capacity in megawatts (MW) from 2010 to 2022, and its interplay with the importation of principal wind energy production components. Understanding the interrelation between the variables above may facilitate forecasting wind energy supply based on import data of the main components of wind farms and the extent of core wind farm elements and the duration of the pre-operational phase (through investment in the import of wind farm components). The first step entailed establishing causality among the study's variables, for which the Granger causality tests proposed by Toda and Yamamoto (1995) were applied. Vector autoregressive models (VAR) were estimated with the variables of installed capacity in MW and Import of the most important components for the implementation of wind farms, both on a logarithmic scale (ln). The findings indicated that there is no evidence to reject H_0; that is, the hypothesis of no causality from Installed Capacity to Import was not rejected. Conversely, according to the applied test considering that Import does not cause Capacity, the null hypothesis (H_0) was rejected with a p-value of (0.00096). Thus, the tests showed unidirectional Granger causality from the Import variable to the Capacity variable, suggesting that the import of key wind farm components is a determinant for installed capacity in MW.

Subsequently, several Neural Network configurations were applied to forecast the Installed Capacity in megawatts (MW) of Brazilian wind energy, one univariate and several multivariate. As stated above, the multivariate model formulation provides a closer approximation to real values. The neural network containing the variation of installed capacity in megawatts (MW) in the previous period and the variation of the monetary volume allocated to the import of the main components of wind farms at different lags (1, 3, and 6 lags) showed lower error measures. Therefore, it proved more efficient than the network that contained only the series of variations of the Installed Capacity in megawatts (MW). Additional outcome of this research was applying the method described in [26], which assessed the relative importance of explanatory variables for a single outcome variable within a neural network by deconstructing the model's weights. The relative importance (or strength of association) of a specific explanatory variable for the response variable can be determined by identifying all the weighted connections between the nodes of interest. Each weight linking the specific input node through the hidden layer to the outcome variable is documented. Based on the analysis, the most critical variable in configuration (equation 2) is the variation of Installed Capacity in megawatts, followed by the variations of Imports of components for wind energy production with a lag of 3, 1, and 6 months.

Using the Lek profile method, it was observed that the monthly import variable exerts the same pattern of influence in all groups except for group 1. Within groups 2 to 6, the accumulated import variables of three months and six months markedly affect the installed capacity of wind farms.

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