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APPLICATION OF THE NARX MODEL FOR FORECASTING WIND SPEED FOR WIND ENERGY GENERATION

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ABSTRACT

The wind energy matrix has been gradually increasing in recent years and its importance for the renewable energy industry is increasingly linked to benefits in relation to the environment. The objective is to apply the NARX model to forecast wind speed in the short term and consequently the generation of wind energy. In the materials and methods, the database of the SONDA project (System of National Organization of Environmental Data) organized by INPE (National Institute for Space Research) was used, in which it was decided to use the anemometric data of the Brasília station - BRB, where data from February 2005 to March 2019 were used for validation training and testing of the model developed. The results obtained were characterized by a better performance for the short-term time horizon of 10 minutes up to 10 steps ahead, which helps to provide the wind energy industry with greater reliability in energy delivery.

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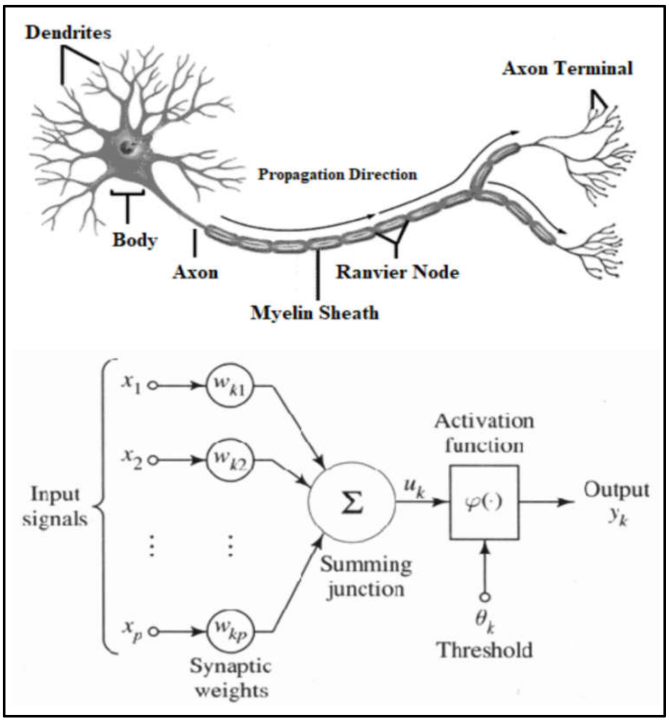
INTRODUÇÃO

Brazil's renewable/alternative energy matrix has been growing over the years (SANTANA *et al.*, 2020; BARBOSA DE ALENCAR *et al.*, 2017). AccordinglySilva *et al.* (2017),there are four main factors for this growth, which are: Wind characteristics in the country, incentive policies for the generation of wind energy, competitiveness generated by the wind sector and, consequently, competitive prices in relation to non-renewable sources. Another factor that makes wind power generation a high-growth source in Brazil and in the world is the issue of the environmental impact caused and self-sustainability. In view of these aspects that directly impact on the energy matrix as a whole, it is extremely important to predict the wind speed for a given time horizon, since knowing the wind speed it is possible to calculate the energy generation in an interval of time in the future, thus avoiding the generation of electric energy by sources that harm the environment more strongly. Forecasting wind power is necessary for good wind farm planning, including maintenance of wind farms and networks, dispatch of generating units, sale of energy, service of cargo and other benefits (BARBOSA DE ALENCAR *et al.*, 2017), while it is complex to forecast with good accuracy due to instability, seasonality, non-linearity and sudden gusts of wind (DONG, SUN eLI, 2017). The present work is justified by the relevance that the studied energy matrix has in the Brazilian and foreign scenario, in addition to the forecast of the wind speed being an extremely important factor to plan the amount of electric energy to be generated in the next periods of time. The work aims to develop a hybrid model for forecasting the wind speed and consequently the generation of wind energy, based on the AutoRegressive Non-Linear Neural Network with Exogenous Inputs (NARX).

THEORETICAL REFERENCE

Wind Energy: Accordingly Silva (2003), one of the most important benefits of wind energy is the decrease in carbon dioxide (CO_2) released into the atmosphere. Soon this source has relevance in the environmental aspect and linked to the growth of this source in the energy matrix, there was an increase in works related to the forecast of wind speed and electricity generation in recent years. For the forecast of wind energy, there are some time horizons to be forecast, each one with a specific purpose, the most used are short-term and long-term forecasts. The short-term forecast extends over an interval of 30 minutes to 6 hours, this type of forecast serves mainly to dispatch the generating units, sell energy, service the load and among other purposes (BARBOSA DE ALENCAR *et al.*, 2017), while the long term is associated with periods longer than 1 week to 1 year, in which it has purposes such as the maintenance of electrical networks and even wind farms, in addition to the planning of building wind farms (LEI *et al.*, 2009).

Artificial Neural Networks: Artificial Neural Networks were first established in 1943 (MCCULLOCH e PITTS, 1943), they are based on human neurons and try to mimic the behavior of the brain to predict future events based on an experiment or sample of data.AccordingBarros *et al.*, (2018),the representation of an artificial neuron is identical to a biological neuron, having some characteristics in common, such a comparison between neurons can be seen in Figure 1.



Source: Adapted from Barros *et al.*, (2018).

Figure 1. Comparison between biological and artificial neurons

There are some variants of RNA and one of them is used in the hybrid model proposed in this article, which is the recurrent model of Neural Network known as Non-Linear AutoRegressive with Exogenous Inputs (NARX), used for time series (MATKOVSKYY e BOURAOUI, 2019; WUNSCH, LIESCH e BRODA, 2018; CARPINTEIRO *et al.*, 2006). This variation of RNA receives external input data as well as data resulting from the output of the network itself, so the final result is a function of time (SOUZA *et al.*, 2019). Equation 1 represents the mentioned network model.

$$\hat{y}(k) = F\big(u(k-1), \dots, u(k-n), y(k-1), \dots, y(k-m)\big) \quad (1)$$

Where:

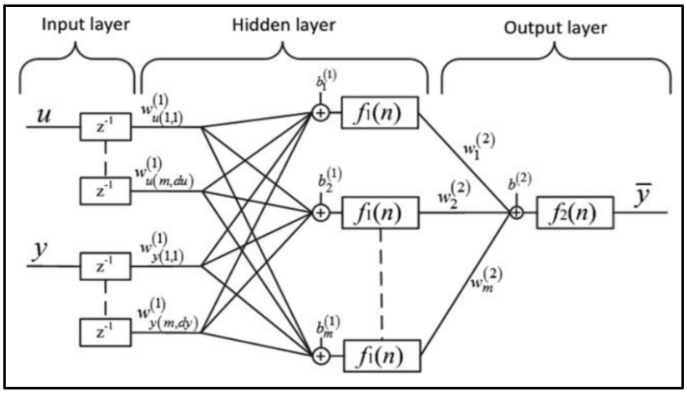
u = External input on the network;
y = Previous network response;
$\hat{y}$ = Estimated network output.

In Figure 2, the architecture of the AutoRegressive Nonlinear Neural Network with Exogenous Inputs (NARX) is presented in detail.

Levenberg-Marquardt Training Algorithm: The Levenberg-Marquardt algorithm was formed in two stages, the first in 1944 by Levenberg and was complemented and completed by Marquardt in 1963, hence the name of the algorithm (LM-Levenberg-Marquardt) (HENNINGSEN, HENNINGSEN e WERF, 2019). Levenberg-Marquardt is widely used as a training algorithm in Artificial Neural Networks, as it is considered by many authors to be the fastest algorithm, but it is worth noting that it needs more computational power to perform the optimization than most other algorithms (GONÇALVES *et al.*, 2010). This algorithm has its main application focused on the problem of adjusting the least squares curve (DADA *et al.*, 2021), where the problem can be represented by Equation 2:

$$\hat{\beta} \in argmin_{\beta}\ S(\beta) \equiv argmin_{\beta} \sum_{i=1}^{m} [y_i - f(x_i, \beta)]^2 \quad (2)$$

Where:
β = Parameters;
m = Empirical pairs;
x_i= Independent Variables;
y_i = Dependent Variables;
$f(x_i,\beta)$ = Model;
$S(\beta)$ = Deviations;



Source: AGUILAR-LOBO *et al.*, (2015).

Figure 2. NARX architecture

Bayesian Regularization Training Algorithm: The Bayesian Regularization training algorithm is a model that transforms a non-linear regression to a statistical model, with the benefit of not using validation and its robustness. Thus, RNAs and their variations that use Bayesian Regularization are more robust than those that use the backpropagation training algorithm, precisely because it is not necessary to do the validation step (BARROS *et al.*, 2018).

The equation that defines the Bayesian Regularization networks is given by Equation 3.

$$F = \beta E_D + \alpha E_W \quad (3)$$

Scaled Conjugate Gradient Training Algorithm: The Scaled Conjugate Gradient algorithm is a model for learning and is widely used for training ANNs, this algorithm works as the basic principles of optimization, having an objective function and converging to the target, but the control of the size of steps that the same targeting is more efficient when it comes to second-order information (BARROS *et al.*, 2018).

Equation 4 represents the mathematical model of the model.

$$E_{qw}(y) = E(w) + E'(w)y + \frac{1}{2}y^T E''(w)y \quad (4)$$

Forecast Models: Some models have been developed over the years in an attempt to increasingly improve the prediction of wind speed, among the most well-known models in the literature can be mentioned: Artificial Neural Networks (AHMED e KHALID, 2017; DUAN *et al.*, 2021), AutoRegressive Integrated Moving Average (ARIMA) (SINGH *et al.*, 2019; SINGH, SINGH e NEGI, 2019), Exogenous Integrated AutoRegressive Moving Average (ARIMAX) (XU *et al.*, 2019), Holt-Winters (KALEKAR *et al.*, 2004), Integrated AutoRegressive Seasonal Method Moving Average (SARIMA) (PONGDATU e PUTRA, 2018; ALENCAR *et al.*, 2018). In addition to renowned models, there is an increasing number of works being published with hybrid models (ALTAN, KARASU e ZIO, 2021; ZHANG, WEI e TAN, 2020; LIU *et al.*, 2020; CHEN *et al.*, 2021; MALIK e YADAV, 2021), increasing performance compared to simple models that use only one technique.

MATERIALS AND METHODS

For the development of the NARX forecasting neural network, a study of the main forecasting techniques was carried out, in which NARX was selected for working with time series forecasts with a good performance, with NARX being a recurring RNA. The database used was the data from the SONDA project (System of National Organization of Environmental Data) organized by INPE (National Institute for Space Research), in which it was decided to use the anemometric data from the Brasília station - BRB, where they were used data from February 2005 to March 2019 were used for validation training and testing of the model developed. According to SONDA (2021), an assessment is made of the reliability of the collected data, due to some factors such as equipment malfunction, lightning or even accidents with animals, following the data quality control strategies used by the Baseline Surface Radiation Network (BSRN) together with criteria established by Webmet (http://www.webmet.com/).

Development Steps

Data Normalization: The data are normalized by SONDA itself, however due to some errors in the anemometric equipment, the collection had some data that was not possible to capture, so it was necessary to make a new normalization in the data, so that there was a greater reliability of the real data and not there were gaps between one data and the other.

Implementation of the Algorithm: For the implementation of the algorithm, the software *MatLab®* in its version 2016 was used, which is a highly recognized software in the international scenario and was chosen because it has a toolbox of the NARX model, facilitating the implementation of the algorithm.

Error: The Mean Square Error (MSE) and the Square Root of the Mean Square Error (RMSE) can be defined by Equation 13 and 14 respectively.

$$MSE = \frac{1}{N}\sum_{k=1}^{N}(SoC_{th}(k) - SoC(k))^2 \quad (13)$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{k=1}^{N}(SoC_{th}(k) - SoC(k))^2} \quad (14)$$

The MSE and RMSE are indicators used to show how accurate the analyzed numbers are, and the closer to zero the better the accuracy, if equal to zero, indicates a perfect accuracy of 100% (BHARDWAJ *et al.*, 2013). Both MSE and RMSE are positive with the lowest possible value being zero. Another statistical method to evaluate the network performance is the Mean Percentage Absolute Error (MAPE) (KAUSHIKA, TOMAR e KAUSHIK, 2014), which is given in percentage and can be defined by Equation 15, the smaller the error, the better the performance.

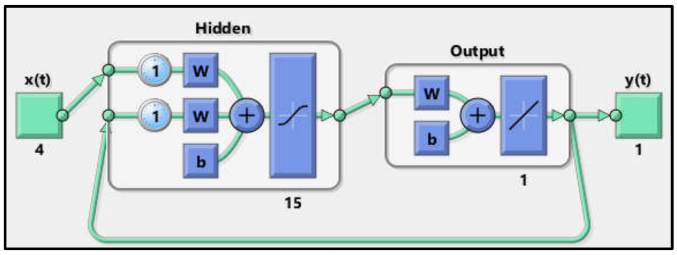
$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\frac{y - x}{w} \times 100 \quad (15)$$

Where:
x = Input data;
y = Data predicted by the network;
w = Number of vector elements.

RNA Architecture (NARX) Used: Figure 3 shows the architecture of the NARX network used in the hybrid model, configured with 4 input and 1 output variables. The variables used in the entry:

Atmospheric pressure;
Relative humidity;
Wind Direction;
Air temperature.

As for the target to be found, the variable Wind speed was used.



Source: Authors, (2021).

Figure 3. Architecture and configurations used in the NARX network

The network was configured with 4 inputs and an output, having a hidden layer with 15 neurons. It is worth mentioning that this network structure was applied to all tested scenarios. The network was trained with three algorithms being (LM) (BS) and (SCG) and a comparison was made between the three to obtain the best of the algorithms in the tested time horizons. 70% of the data were used for training, 15% for validation and 15% for tests. The amount of data used for each variable of the scenarios presented is shown in Table 1.

The data comprise a date range from 29-Jan-2018 09:07:00 to 31-Mar-2019 23:59:00. Table 2 shows a sample of data used, in which data are collected every 1 minute by the anemometers of the wind towers in the BRB park.

Table 1. Amount of data used

Horizon	Amount of data used
10 minutes	4558
1 hour	9389
1 day	18391

Source: Authors, (2021).

The data used are categorized by Year, Day, Hour, Minute, Temperature, Humidity, Pressure, Wind Speed and Wind Direction. Some important characteristics to take into account are:

Minute: The minutes are sequential and collected every 1 minute by anemometers;

Temperature: The temperature is given in degrees Celsius at 25 meters high;

Relative Air Humidity: It is given in percentage (%), being a meteorological variable;

Wind Direction: The wind direction is given in degrees Celsius at a height of 25 meters from 0º (North) to 360º (Clockwise);

Atmospheric Pressure: It is given in millibars, as well as in the relative humidity of the air, it is also a meteorological variable;

Wind Speed: It is given in milliseconds (ms-1) at a height of 25 meters.

RESULTS AND DISCUSSIONS

Three training algorithms were used in the NARX network, in which Bayesian Regularization (BS), which in the literature is the training algorithm that has the best performance in convergence and results, proved to be true also in the tests performed, compared to the Levenberg- Marquard (LM), which is also widely used and has excellent performance and the Scaled Conjugate Gradient (SCG), the performance of each algorithm can be seen in Table 3.

Table 2. Sample data

Year	Day	Hour	Minute	Temperature	Humidity	Pressure	Wind Speed	Wind Direction
2019	1	1	0	19,84	93,8	897,65	0,231	320,5
2019	1	1	1	19,64	93,9	897,64	0,272	318,2
2019	1	1	2	19,54	93,8	897,64	0,179	317,4
2019	1	1	3	19,67	93,8	897,64	0,171	316,4
2019	1	1	4	19,62	93,8	897,64	0,228	308,1
2019	1	1	5	19,41	93,8	897,72	0,274	303,2
2019	1	1	6	19,35	93,7	897,72	0,314	298,6
2019	1	1	7	19,48	93,8	897,64	0,354	291,2
2019	1	1	8	19,56	93,7	897,72	0,398	280,1
2019	1	1	9	19,39	93,7	897,72	0,562	249,5
2019	1	1	10	19,56	93,7	897,8	0,535	249,9
2019	1	1	11	19,56	93,7	897,8	0,568	249,9
2019	1	1	12	19,53	93,6	897,8	0,585	248,1
2019	1	1	13	19,59	93,6	897,8	0,533	231,6
2019	1	1	14	19,38	93,6	897,88	0,516	232,9

Source: Authors, (2021).

Table 3. Result of the training algorithms

Errors	Horizon	Steps forward	Levenberg-Marquard (LM)	Bayesian Regularization (BS)	Scaled Conjugate Gradient (SCG)
MSE	10 minutes	1	1.23714523283	1.15645168863	1.34426047087
RMSE	10 minutes	1	1.112270306	1.075384438	1.159422473
MAPE (%)	10 minutes	1	0.477189043	0.388046236	0.495322162
CORRELATION (%)	10 minutes	1	0.939094	0.943075	0.933509
MSE	10 minutes	5	1.27156994495	1.16812332811	1.26431475330
RMSE	10 minutes	5	1.127639102	1.080797543	1.124417517
MAPE (%)	10 minutes	5	0.419625434	0.318891738	0.376222663
CORRELATION (%)	10 minutes	5	0.937235	0.942482	0.937604
MSE	10 minutes	10	1.23112083533	1.16153717527	1.28254323766
RMSE	10 minutes	10	1.109558847	1.077746341	1.132494255
MAPE (%)	10 minutes	10	0.389015797	0.344734922	0.438895544
CORRELATION (%)	10 minutes	10	0.939339	0.942818	0.936663
MSE	1 hour	1	1.15375442902	1.12050680595	1.44058714095
RMSE	1 hour	1	1.074129615	1.058539941	1.200244617
MAPE (%)	1 hour	1	0.311210288	0.263044486	0.541264763
CORRELATION (%)	1 hour	1	0.945143	0.946725	0.931135
MSE	1 hour	5	1.14166329164	1.12113865183	1.31040353901
RMSE	1 hour	5	1.068486449	1.05883835	1.144728587
MAPE (%)	1 hour	5	0.313900352	0.294558668	0.585361004
CORRELATION (%)	1 hour	5	0.945691	0.946690	0.937412
MSE	1 hour	10	1.13038880141	1.11474732423	1.24116785707
RMSE	1 hour	10	1.063197442	1.055815952	1.114077132
MAPE (%)	1 hour	10	386.326710	300.199419	409.784642
CORRELATION (%)	1 hour	10	0.946242	0.947009	0.940807
MSE	1 day	1	1.30223077835	1.27657212865	1.35602358224
RMSE	1 day	1	1.141153267	1.129854915	1.164484256
MAPE (%)	1 day	1	0.474885257	0.451626268	0.409535589
CORRELATION (%)	1 day	1	0.931249	0.932652	0.928298
MSE	1 day	5	1.31443419108	1.28044627195	1.42212898077
RMSE	1 day	5	1.146487763	1.131568059	1.192530495
MAPE (%)	1 day	5	0.558415097	0.466083675	0.572387884
CORRELATION (%)	1 day	5	0.930775	0.932439	0.924699
MSE	1 day	10	1.28776562060	1.28280244334	1.37924673595
RMSE	1 day	10	1.134797612	1.132608689	1.174413358
MAPE (%)	1 day	10	0.478223752	0.460803051	0.521536453
CORRELATION (%)	1 day	10	0.932039	0.932310	0.927020

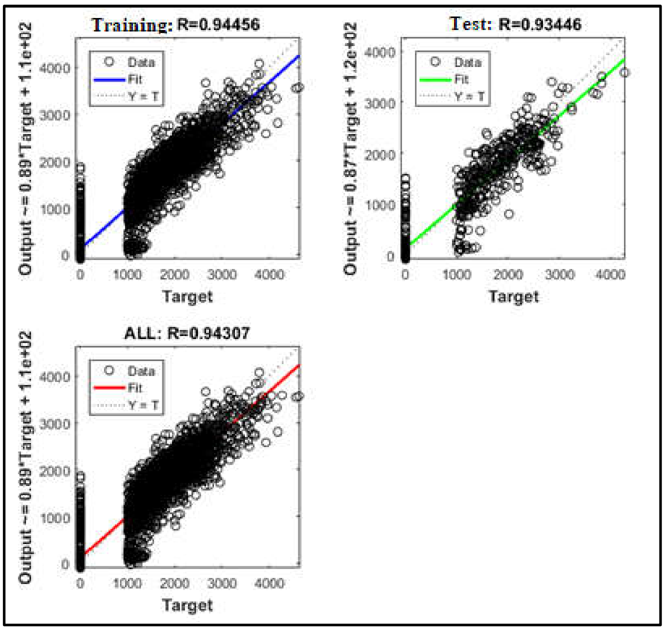
Source: Authors, (2021).

In the tests performed on the NARX prediction model, they performed well in general, mainly for short-term horizons, as can be seen in Table 3, in which it can be seen that the best training algorithm was BS in terms of correlation, achieving the best correlation among the other training algorithms tested in all scenarios. In contrast, the SCG algorithm was the worst in the correlation performance, and it is worth noting that this occurred for all scenarios reproduced. For the MSE the best performance obtained was the BS algorithm, in second place was the LM and lastly the SCG, this occurred in almost all the scenarios tested, the SCG was better than the LM only in one scenario, already indicating that the SCG it is not a great algorithm for forecasting time series with seasonality and trend as is the case of winds. For RMSE it follows the same line of reasoning since RMSE is the square root of MSE.

Among the nine scenarios reproduced, the BS algorithm had a smaller MAPE in eight scenarios, while the SCG had the best MAPE performance in one opportunity. The LM did not obtain a better performance in any of the cases. In view of this performance analysis of the training algorithms, the NARX model has the training algorithm BS, because in general it was the one that presented the best performances.

Model Correlation and Performance: The regression graph shown in Figure 4 shows the correlation between the target to be reached for the dependent variable (Wind speed), with the correlations displayed both for Training and Test as well as the total correlation, with one in training having a correlation of 0.94456 and test 0.93446, reaching a total correlation of 0.94307.

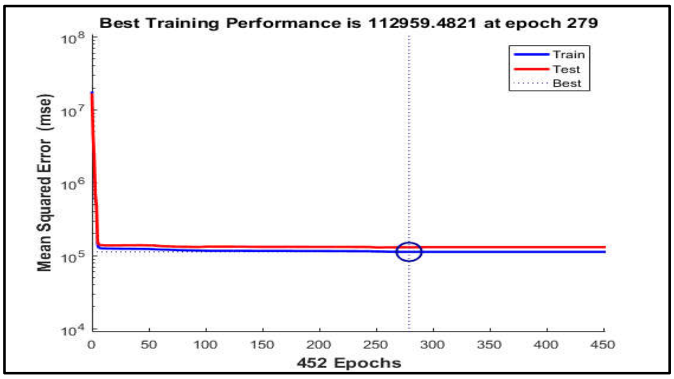
Figure 4 does not show the validation correlation because the BS algorithm does not use validation because it is a robust algorithm.



Source: Authors, (2021).

Figure 4. Correlation graph

As can be seen in Figure 5, the BS has no validation. It had a Training performance of 112959.4821x10^5.

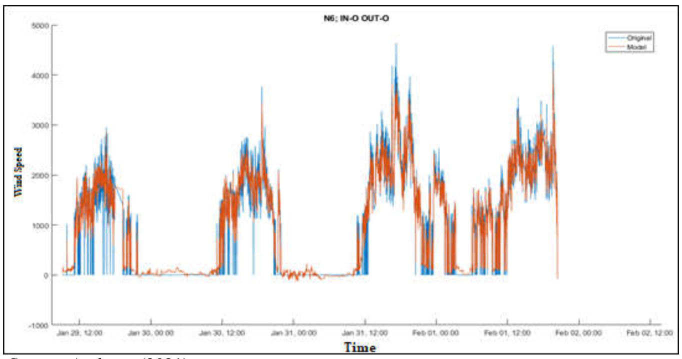


Source: Authors, (2021).

Figure 5. Network training MSE error

One of the characteristics that the BS was not better than the LM is the question of the number of times to reach the target, in all tests it was noted that the number of times performed by the BS was much higher than the LM.

Wind Forecast Result: In Figure 6 the result of the wind speed compared to the original speed is presented in the period from January 29, 2018 to February 1, 2018, the result presented is from the short-term horizon of 10 minutes and 5 steps ahead, or that is, a 50-minute forecast.



Source: Authors, (2021).

Figure 6. Forecast of wind speed by the proposed model

It can be observed that the data sample has a certain seasonality and tendency, this was one of the reasons for using the recurrent NARX ANN, for working well with seasonally data.

CONCLUSION

It is concluded that the work produced reached the established objective of forecasting the wind speed for the short term horizon by the recurrent NARX ANN. The results were satisfactory with the values of the acceptable MSE, RMSE and MAPE errors, in addition to the variables having a high correlation of more than 94%, in which the Bayesian Regularization (BS) training algorithm stood out, surpassing the Levenberg-Marquardt (LM) and the Scaled Conjugate Gradient (SCG). The research tends to enrich and contribute to the forecast scenario in the short term, bringing benefits in terms of reducing the risk of uncertainties in dispatch planning and maintenance in the electricity grid.

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