Comparison of Models for Wind Speed Prediction Through Neural Networks in Lençóis, Bahia

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This study aims to compare forecasting models using artificial intelligence to conclude which is the best one for the forecasting wind speed for 1 hour in Lençóis, BA, using a data source from the Instituto Nacional de Meteorologia (INMET). Furthermore, an Artificial Neural Network (ANN) was developed using TensorFlow and Keras libraries, it was compared with other forecasting models, which showed to be the most efficient among the options for this purpose. Moreover, the principal metric used to evaluate this study was Mean Absolute Error (MAE), and the auxiliary ones were Mean Squared Error (MSE) and R^2. The RNA obtained the following values for each metric: 0.421 for MAE, 0.389 for MSE, and 0.523 for the R^2 metric.
Keywords: Artificial Intelligence. Machine Learning. Neural Networks. Wind Speed. Wind Speed Forecasting.

Introduction

In the current distribution, Brazil has its energy matrix based on hydroelectric sources, with about 63% of total production. However, there is a considerable presence of other methods of energy production since wind energy is about 9% of the energy participation, for instance [1]. Wind energy still has a possible growing outlook because there is a great potential for generation through this type of renewable energy due to the natural characteristics and the size of the Brazilian territory. Furthermore, the hydroelectric power plants may generate environmental impacts, reducing the local fauna and impacting economic activities [2]. With technological and economic development, the importance of the discussion on the implementation of clean and inexhaustible sources of energy is reinforced. Between 2011 and 2019, Brazil invested approximately R$ 187 billion in the wind energy matrix [3], and it triggered an expansion of the participation of this energy source in the country. Wind energy is a sustainable production process, which transforms the energy of air masses into mechanical energy through the force of the winds. Because a problem arises, the wind will not always be favorable for the implementation and activation of wind turbines, and this factor contributes to this source of energy production being less adhered to, as in certain situations it may have low profitability.

Artificial Intelligence (AI) has been progressively assimilated into the daily routine to optimize time to help, solving problems that often cannot be solved with only human capacity. In most cases, artificial intelligence is applied to two types of problems: classification, and regression. In classification issues, the data are used to define which group another specific data fits into, and the regression aims to predict values. Since the 1940s, with the creation of the first neural networks, the complexity and potential of these networks have expanded at an accelerated pace, allowing an improvement in the efficiency of several processes. In February 2019, DeepMind announced a new artificial intelligence program for forecasting energy production in wind farms, executing a practical application of AI in solving an important problem: the unpredictability of renewable energy. The neural network could make a forecast of up to 36 hours about the amount of energy generated by the parks. This attitude increased the value of wind energy produced in those locations by approximately 20% [4]. This example denotes the importance of comparative studies on the efficiency of different neural networks for predicting this type of variable. Its usefulness is evident in solving this problem, considering the importance of this energy source and its character.

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The research was focus on the city of Lençóis-BA, Brazil, a city with 1,277 km² and approximately 11 thousand inhabitants [5]. A comparison was made with different regression models [6], to predict the wind speed in one hour, based on meteorological data provided by INMET (National Institute of Meteorology), corresponding from 2017 to 2019. The models used for comparison were trained and tested for parameter improvement.

Material and Methods

The study algorithm was developed in Python programming language using the Scikit-Learn library. The models were the Stochastic Gradient Descent Regressor (SGD Regressor), Linear Regression, K Nearest Neighbors Regressor (KNN Regressor), and Gradient Boosting Regressor. Besides being compared to each other, an Artificial Neural Network (ANN) of the Multilayer Perceptron (MLP) type was created, using the TensorFlow and Keras libraries, contrasting with the other models.

The dataset used provided by INMET for the city of Lençóis, BA, contains records of the time interval between the years 2014 to 2019, about 46 thousand data, but due to lack of data in the middle of the dataset, that generated intervals in the time series. Only 18 thousand data were considered, referring from 2017 to 2019. This dataset also contained 24 variables. For training, 70% of the data were used during the training stage (30% of this 70% was used for validation), and the remaining 30%, of all, for testing.

The variables, except for the target (Wind, Hourly Speed), were normalized between the 0 and 1 interval with the MinMaxScaler, a data normalizer provided by Scikit Learn. MinMaxScaler works by normalizing the data in the range that is passed, keeping the proportion of the data, where the largest value will be transformed into the highest value passed and the smallest, moreover, into the lowest value, the other values are between this range, keeping the original proportion.

$$Data\_std = \frac{(X - X.min(axis=0)}{(X.max(axis=0) - X.min(axis=0)} \quad (1)$$

$$Data\ Scaler = Data\_std * (max - min) + min$$

Source: Scikit-Learn.

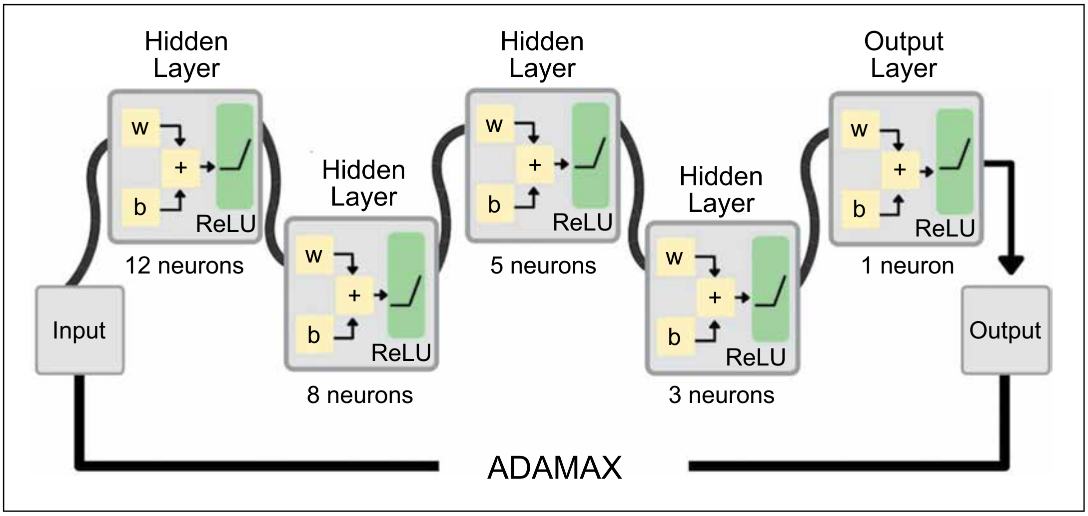
In addition, to determine most of the parameters, the strategy used was to test which combinations of parameters and weights brought improvements to the network, or a reduction in its quality, and with that, the final configurations of the models were found. The neural network (Figure 1) had 5 layers of neurons, including the last layer, the output layer, which contains only 1 neuron, as it is a regression task for a prediction horizon. All layers had the activation function of ReLU (Rectified Linear Unit), which is an activation function widely used in the area of machine learning and was the one that showed the best results. In the output layer, ReLU was also used, because the variable that occurred in the prediction does not contain negative values and this function in the output layer only returns values between 0 and positive infinity. The optimizer used in the network was Adamax, which performed better for this task. During training, 200 epochs were made, and from that, there was no considerable improvement, the batch size used was 100.

The models were also tested to achieve better results than what were seen using their default parameters.

The SGDRegressor (Stochastic Gradient Descent Regressor) had its loss changed from squared loss to squared epsilon insensitive, which presented a better conclusion according to the error metrics. The tool (the stopping criterion) value was reduced by 6 decimal places. So, the model had more training time, and the penalty, also called the regularization term, was changed to l1, and, with that, the model had an improvement in results.

The linear regression model had no parameter changes, as it ended up training better with the pattern, exhibiting lower error values than with customizations.

Figure 1. Structure of the neural network.



Source by authors, 2021.

The KNN Regressor underwent some changes: the number of n_neighbors was changed from 5 to 20, and the weights were defined as distance and metric kept in Minkowski.

The last model, Gradient Boosting Regressor (GradBoost) had its learning rate changed to 0.09. The max depth, which is the maximum depth of the individual estimators, was set to 6 and the number of estimators was changed from 100 to 300, which returned a slight improvement. In your performance.

Thereby, the study tends to compare the efficiency of the models using the following metrics MSE (Mean Squared Error), MAE (Mean Absolute Error), and R^2 score (coefficient of determination), such as metrics were applied by importing tools from the Scikit Learn.

The principal metric used was the mean absolute error, MAE, which calculates the mean between the error module, that is, in its absolute value. Due to its nature of using raw values, this metric is not very efficient in occasions where there is the presence of outliers, which can interfere with the quality of this metric. The smaller the MAE value, the better the model that generated that result was:

$$MAE = \frac{1}{n}\sum_{j=1}^{n} |yj - \hat{y}j| \tag{2}$$

Source: Zucatelli and colleagues, 2018 [8].

The second MSE metric, which represents the root mean square error, is used to check the accuracy of the model. The way to calculate this metric gives greater importance to larger errors, since the values are squared individually, and, only after that, the average between them is calculated, generating higher values for models that present worse results.

$$MSE = \frac{1}{n}\sum_{i=1} |yi - \hat{y}i|^2 \tag{3}$$

Source: Zucatelli and colleagues, 2018 [8].

The last metric that was applied was the R^2 score, from Scikit Learn, a statistical measure of the data distance for the adjusted regression line, the maximum value is 1.0, and it can return values below zero according to the precision of the model, the lower value, the worse the model.

$$R^2 = \frac{\sum_{i=1}^{n} (\hat{y}i - \hat{y})^2}{\sum_{i=1}^{n} (yi - \hat{y})^2} \tag{4}$$

Source: Zucatelli and colleagues, 2018 [8].

Results and Discussion

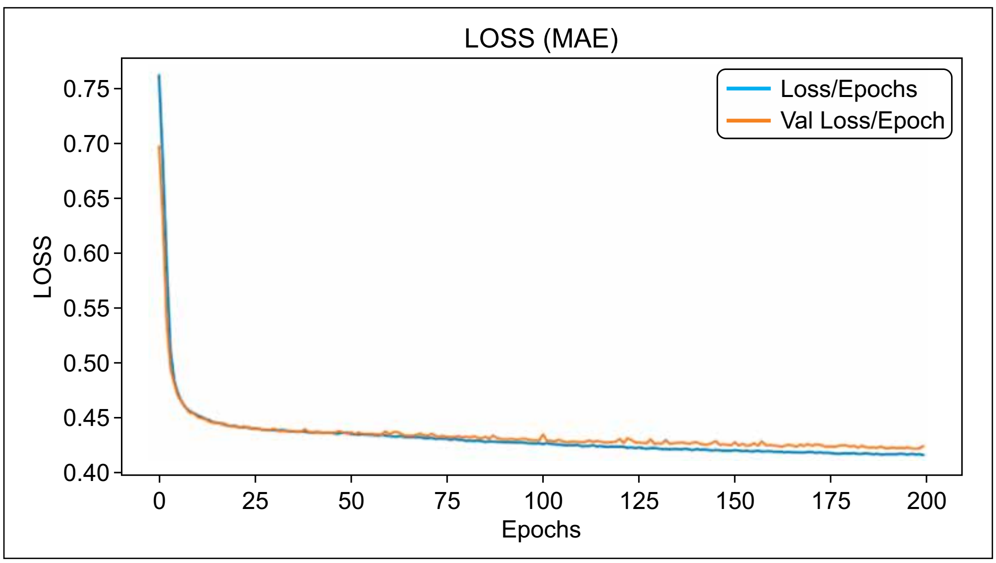
After changes and training, the networks improved their performance for predicting the variable, and the MLP neural network training had a good learning curve, this is represented in the loss graphs (Figure 2). The MAE metric was chosen as a loss metric and MSE (Figure 3), which was the second error metric passed to network training.

The models had similar results, with some distortions in the metrics [7] (Table 1).

Conclusion

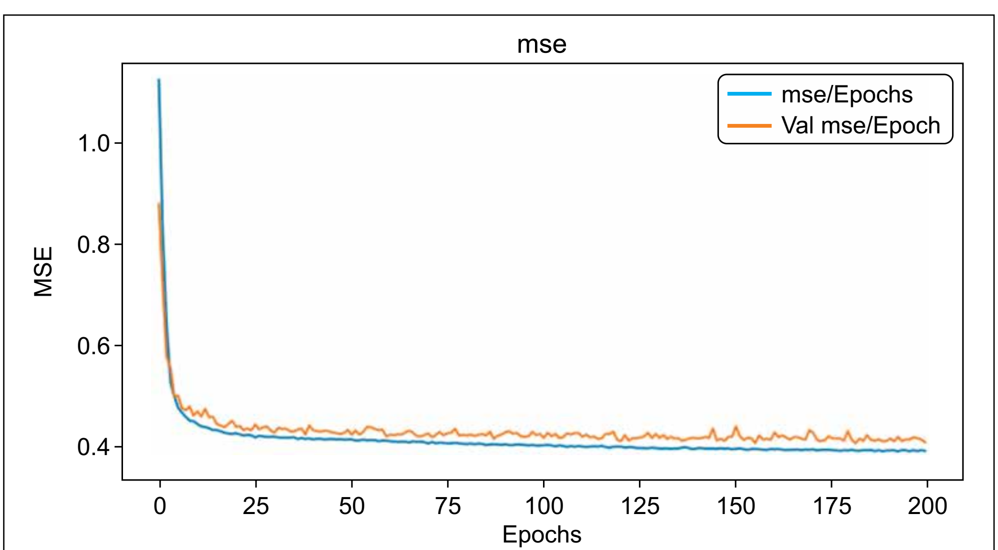
Given the great advances in the technological area and the great need for clean energy and pro-sustainable development are widely disseminated. As aforementioned, a tool capable of predicting

Figure 2. Neural network training loss graph.



Source by authors, 2021.

Figure 3. Neural Network training MSE graph.



Source by authors, 2021.

Table 1. Network results table.

REGRESSION	MAE	MSE	R^2
KNN	0.455	0.378	0.537
MLP	0.421	0.389	0.523
SGD	0.475	0.402	0.507
LINEAR	0.467	0.392	0.555
GRADBOOST	0.439	0.363	0.519

Source by authors, 2021.

wind speed is a great achievement in solving the problem of clean energy sources, becoming essential for reducing the unpredictability of the wind energy matrix, which has great potential, especially in Brazilian territory. Comparing forecasting models and an artificial neural network (ANN). During the process and analyzing the results, the artificial neural network was the most efficient for 1-hour wind speed forecasting, in Lençóis, BA. Considering that the main metric used to contrast the predicting tools was MAE, and on this metric, the ANN showed better results than the other models (0.421) and in other metrics, the results referring to RNA do not differ as much from the others, keeping a result relatively close to the best among the models, having 0.389 of MSE and 0.523 of R^2. Although, for this technology to be used on a large scale and has a more assertive performance, it is expected to get better results from the network with superior computational resources. The potential of this technology can leverage wind energy, making it more widespread worldwide.

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