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A COMPARATIVE STUDY OF FORECASTING TECHNIQUES FOR WIND ENERGY GENERATION

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Abstract. *Alternative energy sources are becoming more and more frequent, aiming to reduce environmental pollution, besides being ideal to overcome the energy crisis. Wind energy is renewable and clean, besides being a source of energy that is permanently available to human beings, that is, it is inexhaustible and occupies the fourth place in the national electric energy matrix. Due to the high level of uncertainty of the factors that directly interfere in the generation of wind energy, such as wind speed, for example, make wind energy predictions with high precision is a big challenge. Therefore, the objective of this article is to develop a model of forecasting through time series that makes it possible to forecast wind energy production. For the development of this comparison, the Auto Regressive with eXogenous Input (ARX) model combined with forecasting models were compared using the error performance measures absolute mean percentage (MAPE) and determination coefficient (R^2). Finally, it is noted that for the training data the Support Vector Machines with Radial Kernel (SVM-RK) and Decision Trees Regression (DTR) models presented the best results, and for the validation data, the SVM-RK model presented the best results.*

Keywords: *Wind Energy, Time Series, Forecasting, Machine Learning, ARX model.*

1. INTRODUCTION

Wind energy is characterized as the generation of energy through the force of the winds, that is, propellers are fixed on top of high towers, which rotate according to the speed of the winds, resulting in the generation of energy through the driving force generated in the wind turbines (NAVRATIL *et al*., 2019). It is noteworthy that wind energy is a source of continuous and sustainable energy, in addition to being able to be built on farms without having to lose agricultural areas. However, the use of such energy also presents some challenges, such as high initial investment costs, the difficulty of transporting wind turbines and the need to carry out an excellent analysis of areas with wind efficiency, and areas with such efficiency are in remote locations and connecting them to the national distribution network requires transmission lines (DEMOLLI *et al*., 2019).

The production of electricity through wind energy, a sector in constant growth, due to the worldwide need to use renewable energies and because it is abundant and available in a clean way, is a factor that depends on the speed of the winds that affect the region (VIANNA NETO *et al*., 2018), a difficult variable to predict because it is fickle. To avoid problems in wind energy estimates, new forecasting models that lead to more satisfactory performances are urgently needed for the operation of energy systems (SUN *et al.*, 2019). In recent years, many different techniques have been applied to forecasting problems. Most of these approaches are algorithms based on machine learning, which have a high capacity to obtain robust results in energy estimation, using different input variables, such as weather conditions and wind speed. Machine learning is a branch of artificial intelligence that believes in the idea what systems can learn from the time series data, in addition to being able to identify standards and make certain decisions (RIBEIRO *et al*., 2020). In the literature Moreno *et al*. (2020), MORENO; COELHO (2018), Moreno *et al*. (2020), also use machine learning techniques to make predictions using wind energy data and other renewable energies, such as solar power (FRACCANABBIA *et al*., 2020), or the prediction of the price of electricity as seen in (RIBEIRO *et al.*, 2020), the price forecast of bitcoin, as (SILVA *et al*., 2020) and forecast of epidemiological time series (RIBEIRO *et al.*, 2020), for example.

This article aims to predict the production of wind energy, applying regression approaches and identifying the techniques that present the best results for the accuracy of the forecast. In addition to developing a forecasting model, through time series, which allows the knowledge of future values of the production of such energy, it is also sought to analyze the machine learning techniques, identifying those that obtain the best results for the forecasting, improving the accuracy of renewable energy production forecasts, identifying more robust models.

In this work, specific methods will be used, which were chosen for their performance and use in the literature, which are Batch-Least-Squares (BLS) (FLEDDERJOHN *et al*., 2010), Artificial Neural Networks - Radial Basis Function (ANN-RBF) (YILMAZ; KAYNAR, 2011) (WANG *et al*., 2020), Support Vector Machines with Radial Kernel (SVM-RK) (RING; ESKOFIER, 2016) and Decision-Trees (DTR) (RATHORE; KUMAR, 2016). Thus, in the sequence, the ARX (YAN *et al*., 2014) (KLINGSPOR *et al*., 2018) (CHEN *et al*., 2020) was applied with the proposed models, which resulted in the models generated for both training and validation.

2. PROBLEM DESCRIPTION

This article aims to forecast the production of wind energy at the Parazinho wind farm, which is equipped with wind turbines with aerogenerators. An aerogenerator is defined as equipment that uses the kinetic energy of the wind, converting it into electrical energy. The wind turbines have as main components (i) the tower, (ii) the rotor, (iii) the generator and (iv) the blades, as illustrated in Fig. 1(b). Besides, it should be noted that there are two basic types of wind rotors: vertical or horizontal axis. The differences between them can be found in the relative cost of production, in the efficiency and in the wind speed in which they have their greatest efficiency. In the present study, the wind turbines are those with a rotor with a horizontal axis, which is the best known and most used due to their greater efficiency. The power range of the wind turbines ranges from 100 W to approximately 8 MW. The equipment in question has a rotor of 100 m of diameter, a static rotational speed of 14.9 rpm, a total of 3 blades and a power regulation that occurs with a regulated pitch with variable speed.

Figure 1(a) - Wind farm location.

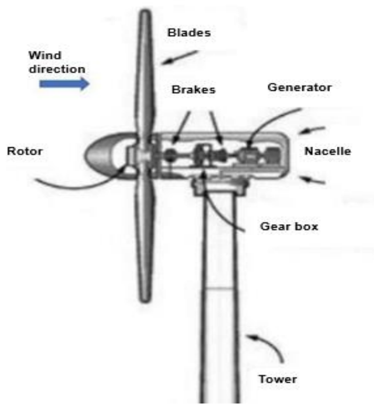


Figure 1(b) - Wind turbine with components.

The dataset used in this case study was collected from a turbine in a Brazilian wind farm, located in the city of Parazinho, in Rio Grande do Norte, as shown in Fig. 1(a). The data refer to the power generation at every 10 minutes, starting on April 2, 2020, at 4:10 pm, and ending on April 7, 2020, at 11:40 pm. Thus, there are a total of 766 observations.

3. FORECASTING TECHNICS

In the literature, several techniques are used to predict variables in engineering and industry problems. Fledderjohn *et al.* (2010) used Batch-Least-Squares (BLS) for estimating Markov parameters. YILMAZ; KAYNAR (2011) and WANG *et al.* (2020) used Artificial Neural Networks - Radial Basis Function (ANN-RBF) for prediction of swell potential of clayey soils and for uncertain distributed force reconstruction considering signal noises and material dispersion, respectively. RING; ESKOFIER (2016) used Support Vector Machines with Radial Kernel (SVM-RK) to perform an approximation of the Gaussian RBF kernel for efficient classification with SVMs, and finally, RATHORE; KUMAR (2016) used Decision-Trees (DTR) for the number of software faults prediction.

Approaching each technique separately, a small analysis is made for each one, since both will be used for the development of this work:

- Batch least squares (BLS) estimation is a very used algorithm in the literature. For example Park *et al.* (2010) were used BLS for a satellite orbit determination system. The basic dynamic and measurement equations for describing estimation algorithms are as follows,

$$x_{k+1} = f(x_k, w_k, t_k) \tag{1}$$

$$y_k = h(x_k, t_k) + v_k \tag{2}$$

where f is the system function, h is the measurement function, x_k is the state vector at time t_k with a covariance of P_k, and y_k is the measurement vector. w_k and v_k are the process noise vector and the addictive measurement noise vector, respectively, which have a zero-mean Gaussian distribution with covariance of Q_k and R_k, respectively. In addition, w_k and v_k are uncorrelated.

- According to Fazelpour *et al.* (2016) who used an artificial neural network with a radial basis function (ANN - RBF) for build a short-term wind speed forecasting, ANN-RBF is a type of neural network in which the activation functions are radial basis functions. RBF artificial neural networks generally consist of three layers: an input layer, a hidden layer with nonlinear RBF activation functions, and a linear output layer. In Fig. 2, ilustrates the ANN-RBF structure.

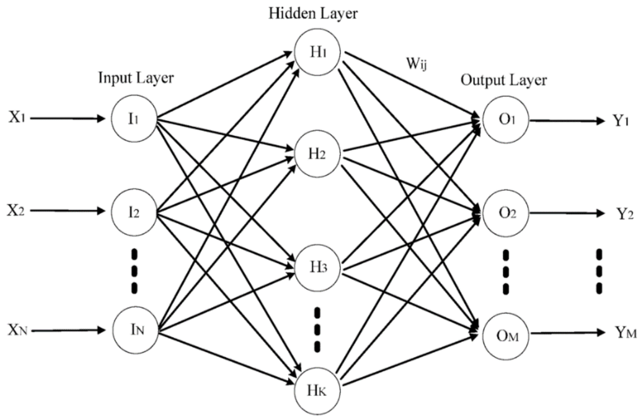


Figure 2 - Autor Cheng *et al*. 2015.

The advantages of using ANN-RBF are the simplicity of the equation structure and the good results what can be reached because of the optimization of the parameters in back-propagation effect.

- SVMs (Support Vector Machines) can be characterized as a set related supervised learning methods popular in performing classification and regression. Each specific method varies according to the structure and attributes of the classifier, the most well-known SVM being a linear classifier. In more detail, SVM creates a hyperplane or set of hyperplanes to classify all entries in a space high dimension (RING; ESKOFIER, 2016). The SVM technique depends on the functions of the kernel, and the kernel is a function used to map smaller data points to larger data points. There are some types of kernel, such as linear, radial and polynomial. In this case, the SVM-radial (SVM-RK) technique is used.
- A decision tree is a decision support tool that uses a decision model similar to a tree and its possible consequences, including results of chance events, resource costs and utility. Thus, it can be said that it is a way to display an algorithm that contains only conditional control instructions. It is noteworthy that the main advantages of the decision tree algorithm are the high classification accuracy and strong robustness (ZHOU *et al*., 2021). Decision trees are commonly used in operational research, specifically in decision analysis, to help identify a strategy most likely to achieve a goal. In addition, it is worth noting that decision trees are a very popular tool in machine learning.

In literature, it is possible to find works related to wind energy predictions using the ARX model, such as (LIN *et al*., 2015) and (LYDIA *et al* ., 2015). The ARX model means autoregressive with exogenous variables or autoregressive with extra inputs since it includes an input term, which differentiates it from the AR model (ISAKSSON, 1993). The structure of the time series models for multiple inputs and the single output ARX model is given by:

$$y(t) = -a_1 y(t-1) - a_2 y(t-2) + \cdots b_1 u(t-1) + b_2 u(t-2) \ldots + e(t) \tag{3}$$

Where u(t) is the exogenous variable at time t, where $b_1 + b_2$ ... are the parameters of the exogenous (X) input part.

To work with the proposed problem, a combination of ARX with machine learning forecasting techniques will be used. The use of ARX is interesting because using data from the past can compensate for the absence of data on variables that we cannot measure or access. Thus, in the sequence, the ARX was applied with the proposed models, which resulted in the models generated for both training and validation. When studying this topic in the literature, it was possible to find authors who use ARX combined with machine learning techniques, such as Potočnik *et al.* (2019) that made use of ARX, neural networks and machine learning to perform the temperature forecast in buildings in the short term. In addition to it, Lin *et al.* (2015) who used ARX for machine learning and random forests for seasonal analysis and wind energy forecast.

4. METHODOLOGY

4.1 Framework

For this work, a framework was proposed where a set of data was used described in section 2. After collecting these data, a normalization and separation treatment between test and validation data was performed. Next, a correlation matrix described by (KUHN; JOHNSON, 2013) was used to determine whether the output variable (power) is sensitive to the input variables. Advancing to the correlation matrix (Tab. 1), a conversion is made from the system that was MISO (Multiple Input Single Output), to a SISO (Single Input Single Output), having the wind speed as input and the generated power as output. It is noteworthy that a correlation of less than 0.5 is weak. Completing this step, regression techniques were applied in conjunction with ARX to generate forecasting models. Fig. 3 illustrates the presented framework.

Table 1 - Data Correlation Matrix

Power	Wind Speed	Wind Direction
1.0000	0.8274	-0.0349
0.8274	1.0000	-0.1984
-0.0349	-0.1984	1.0000

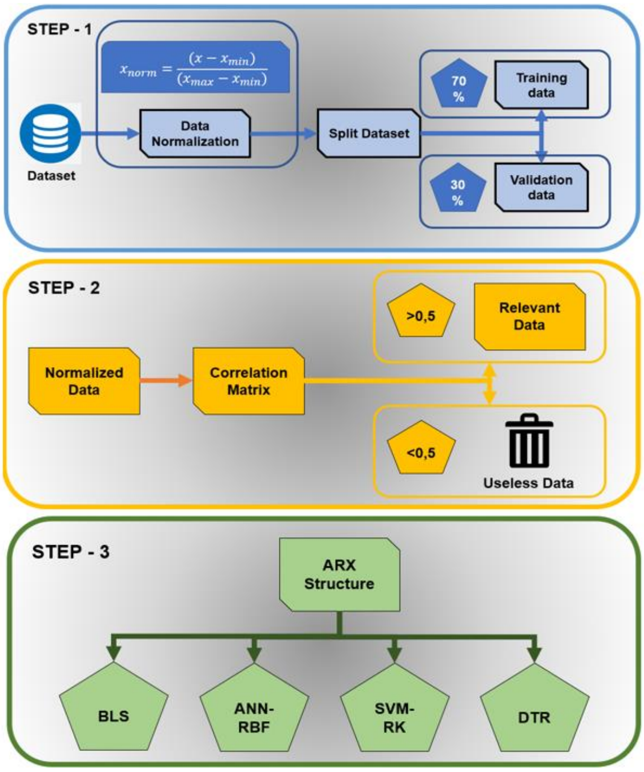


Figure 3 - Framework.

Once the models are generated, the values of MAPE and R^2 will be compared. This performance measurement was obtained according to the following expressions:

Determination Coefficient (R^2) can be considered a multiple correlation coefficient, that is, the correlation between the dependent variable and the set of independent variables (RIFFENBURGH, 2012), given by the formula below. Its value is between 0 and 1, and the higher the value, the better the agreement between model and observation:

$$R^2 = 1 - \frac{\sum_{i=1}^{n}[y_i(t)-\hat{y}_i(t)]^2}{\sum_{i=1}^{n}[y_i(t)-\bar{y}(t)]^2} \tag{4}$$

Mean Absolute Percentage Error (MAPE) is used to measure the error in percentage, (GOODWIN; LAWTON, 1999). MAPE has a vast facility of interpretation, due to fact to be expressed in percentage terms. Besides, its formulation is given by:

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{y_i(t)-\hat{y}_i(t)}{y_i(t)}\right| \tag{5}$$

where n represents the number of observations from the training and validation sets, y_i represents the i-th observed value and $\hat{y}_i$ the i-th predicted value.

Modelling an event or a system isn't a science who has a well defined methods and techniques for every problem. So, there is kind of art from who is building a model. To build an ARX models there is a lot of ways used by researchers. Valer (2016) and Matos (2018), used the Partial Autocorrelation Function for estimating lags of Autoregreessive (AR) therms for input and output system variables. They use the second higher value of PACF to determine de AR lag value of a variable. In this work, it'll be used the same approach.

4.2 Development

In the present study, 30% of the data were used for training and 70% for validation, to develop a model and validate its use. Then, using the correlation matrix illustrated in Tab. 1, a system was determined with input with wind speed and output as power. To continue the work, significant delays were made for the accuracy of the forecast, using the partial autocorrelation function (Fig. 4). Then, analyzing the figure, it is noticed that for the input, lag 4 presents a more significant behavior concerning those that appear in the sequence. Thus, the system order is delimited as autoregressive (AR) equals to 4. In the case of the output, it is possible to notice that lag 3 is the one that has a more significant behavior than the others. Thus, the order of the system will be AR equals to 3.

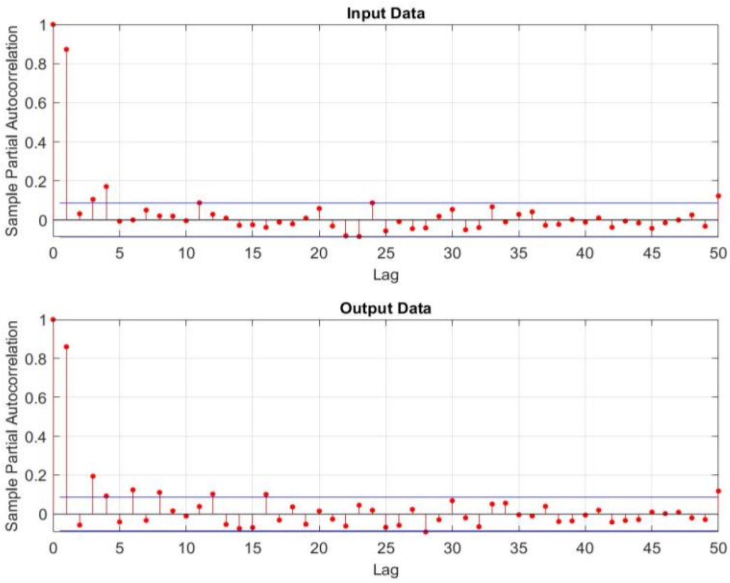
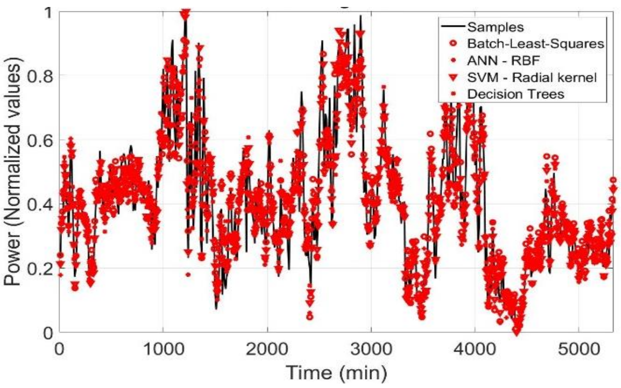
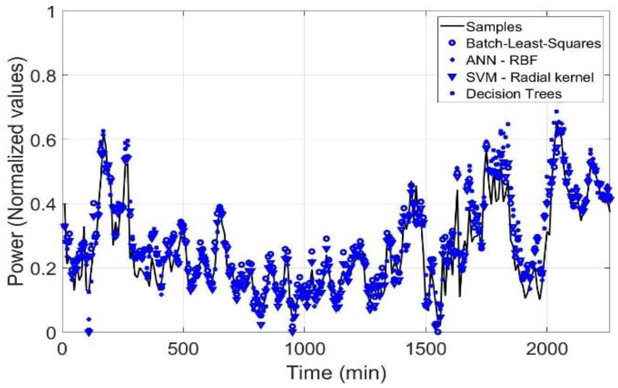


Figure 4 - Analysis of the partial autocorrelation function for input and output data.

After determining the structure of the lags that will be used in the ARX model, the regressors described in section 2 were applied. The Fig. 5 illustrate the behaviors for training and validation.



(a)



(b)

Figure 5 – Models plots (a) training and (b) validation data.

5. RESULTS

Finally, some preliminary results were found. When analyzing which method presents the best results for the present study, it was possible to obtain the results presented in Tab. 2, which describe the performance measures of the models and compare the training and validation values. Also, in Fig. 6 it is possible to observe an exemplification of the data presented in Tab. 2, in which the training is represented in red and the validation in blue. According to the indicators of the generated models, it can be concluded that for the training data the SVM-RK and DTR models presented the best results, whereas for the validation data the best model was the SVM-RK.

Table 2 - Fitness and error performance of used models.

Indicators	R^2		MAPE (%)	
Models	Training	Validation	Training	Validation
BLS	0.8730	0.8139	18.2561	24.7696
ANN-RBF	0.8864	0.8125	17.2796	22.8431
SVM-RK	0.8910	0.8390	16.3502	21.6992
DTR	0.9011	0.7585	20.0850	24.8830

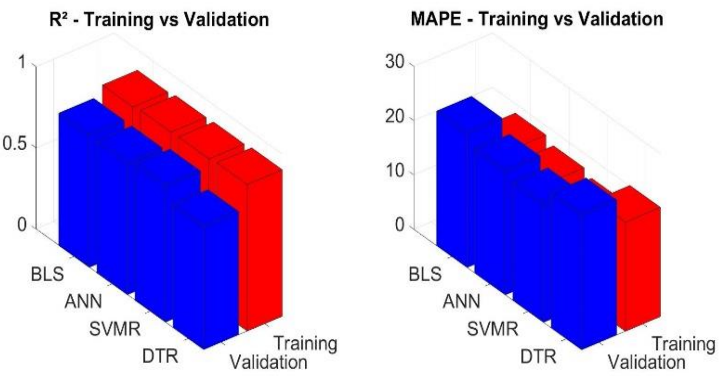


Figure 6 – Exemplification of fitness and error performance of used models.

Histograms illustrated by Fig. 7 were also generated to measure the error of the generated models

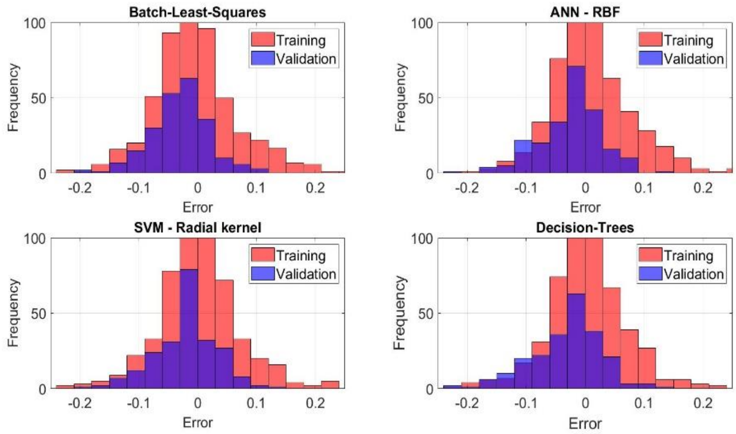


Figure 7 - Histogram of errors - Test and Validation.

After generating the models, they were compared for the MAPE and R^2 values, in order to identify the best models. Then finding the best models for forecasting wind energy, analysis of the samples is made with these models. In Fig. 8 are found the plots of the models that presented the best results, in which it is possible to observe the accuracy of the SVM-RK and Decision-Trees about the training data and later, the accuracy of the SVM-RK concerning the validation data.

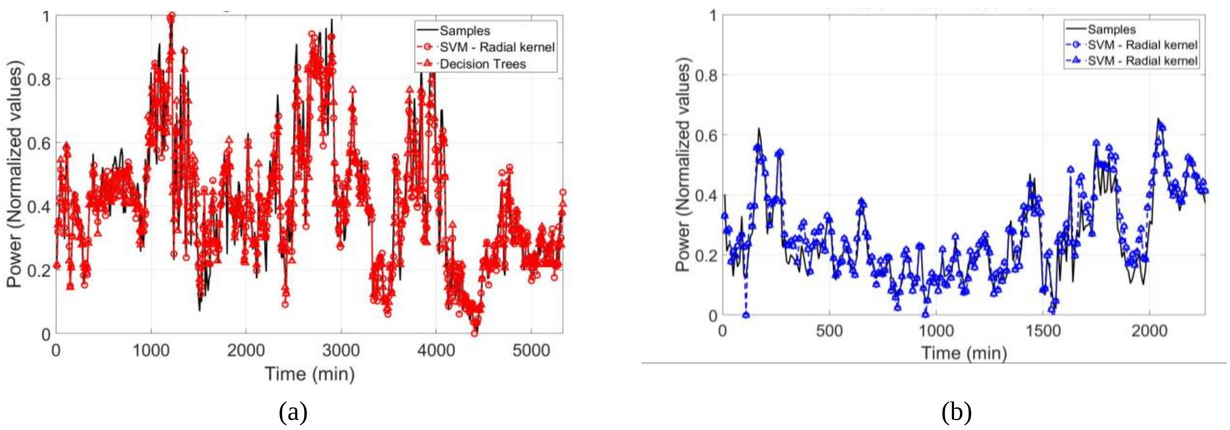


Figure 8 – Best model plots (a) training and (b) validation data – best R^2 and MAPE.

Afterwards, histograms illustrated by Fig. 9 were generated to measure the error of the best generated models.

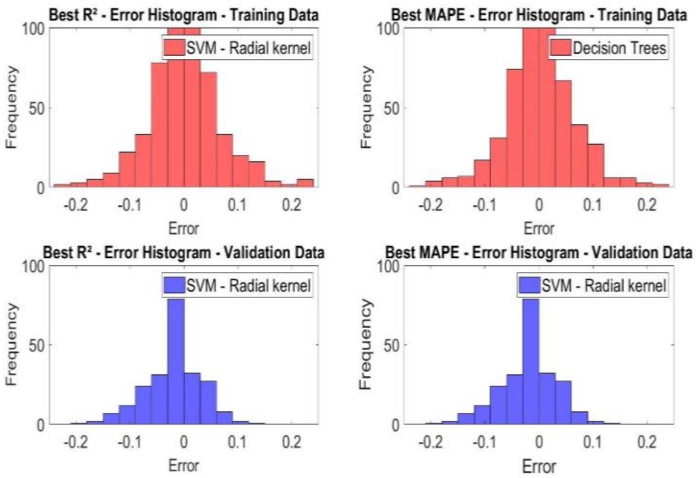


Figure 9 - Histogram of the best generated models - Test and Validation.

looking at the histograms illustrated in Figure 9 it is possible to observe a normal behavior of the MAPE and R^2 values. This behavior illustrates a randomization around statistical interval, it means that our MAPE and R^2 didn't have any distortion in data.

5.1 Statistical tests

Finally, in Tab. 3, which presents the statistical tests and their performance between the test and validation data, the following conclusions are drawn: Looking at the first part of the table, it can be seen that there was variation between test and validation errors. Already when analyzing each column in Tab. 3, it can be concluded that ADF rejected, in all columns, the null hypothesis that there is a unit root, which represents an argument in favor of stationarity. The columns referring to the KPSS show that there was a note of stationarity for some models. Finally, Wilcoxon performed well in training and validation and Friedman points out that in most cases there was a significant variation in the error.

Table 3 - Statistical Tests: Performance Between Test and Validation Data.

	Model	Friedman	Wilcoxon	ADF	KPSS
Models	Hypotesis Testing	prob > Chi-Sq	p-value > P	p-value > P	p-value > P
	BLS	0.0013 > 10.2796	8.6522E-03 > 0.05	0.001 > 0.05	0.01 > 0.05
	ANN-RBF	8.5842E-09 > 33.1381	4.6339E-06 > 0.05	0.001 > 0.05	0.01 > 0.05
	SVM-Rk	1.5147E-06 > 23.1292	3.6096E-05 > 0.05	0.001 > 0.05	0.01 > 0.05
	DTR	2.2985E-09 > 35.7027	5.1769E-06 > 0.05	0.001 > 0.05	0.01 > 0.05
Statistical Tests - Performance trough the Test Data					
	Model	Friedman	Wilcoxon	ADF	KPSS
Models	Hypotesis Testing	prob > Chi-Sq	p-value > P	p-value > P	p-value > P
	BLS	1.0000 > 0.0000	0.0000 > 0.05	0.001 > 0.05	0.01 > 0.05
	ANN-RBF	0.9024 > 0.0150	0.0150 > 0.05	0.001 > 0.05	0.01 > 0.05
	SVM-Rk	0.6238 > 0.2404	0.2400 > 0.05	0.001 > 0.05	0.01 > 0.05
	DTR	0.9024 > 0.0150	0.0150 > 0.05	0.001 > 0.05	0.01 > 0.05
Statistical Tests - Performance trough the Validation Data					
	Model	Friedman	Wilcoxon	ADF	KPSS
Models	Hypotesis Testing	prob > Chi-Sq	p-value > P	p-value > P	p-value > P
	BLS	0.0013 > 10.2796	8.6522E-03 > 0.05	0.001 > 0.05	0.1 > 0.05
	ANN-RBF	8.5842E-09 > 33.1381	4.6339E-06 > 0.05	0.001 > 0.05	0.0434 > 0.05
	SVM-Rk	1.5147E-06 > 23.1292	3.6096E-05 > 0.05	0.001 > 0.05	0.0524 > 0.05
	DTR	2.2985E-09 > 35.7027	5.1769E-06 > 0.05	0.001 > 0.05	0.011 > 0.05

6. CONCLUSION

This article aims to predict the production of wind energy, using a database collected in a Brazilian wind farm. The work covered data related to wind energy due to the growing demand for the use of renewable energy and because it is a natural resource available all over the planet. For the development of the proposal, the ARX model combined with forecasting models were compared using the MAPE and R^2 performance measures. Finally, it was concluded that for the training data the SVM-RK and DTR models presented the best results, and for the validation data the SVM-RK model presented the best results. As a future work, it is proposed to increase the number of steps ahead, in addition to testing other methods, aiming increasingly for better accuracy in predictions.

7. ACKNOWLEDGEMENTS

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