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WIND ENERGY MULTI-STEP AHEAD FORECASTING BASED ON VARIATIONAL MODE DECOMPOSITION

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Abstract. *Wind energy is one of the sources which still in development in Brazil, however, it already represents 17% of the National Interconnected System. Due to the high level of uncertainty and fluctuations in wind speed, prediction of wind energy with high accuracy is a challenging task. In this context, this paper proposes a framework that combines Variational Mode Decomposition (VMD) based on Machine Learning algorithms to forecast the wind energy of a turbine in a wind farm at Parazinho city, Brazil, using a multi-step-ahead forecasting strategy. The forecasting models of the wind energy time series are Bayesian Regularization of Artificial Neural Networks, Cubist Regression, and Support Vector Regression. The performance of the proposed forecasting model, named VMD–CUBIST, was evaluated by using two performance metrics: symmetric mean absolute percentage error, and relative root mean square error. The VMD–CUBIST model outperforms the VMD, and single models in all forecasting horizons, with a performance improvement that ranges 3.00% - 83.30%. Indeed, VMD–CUBIST is an efficient and accurate model for wind energy forecasting. forecasting.*

Keywords: *Wind energy, Time series forecasting, Variational mode decomposition, Machine learning*

1. INTRODUCTION

Wind energy has been increasing its operation in the energy matrix in the last decades in many countries around the world. Even in Brazil, whose electrical power system is majority composed by hydroelectric systems, the wind energy already has a great parcel of the national energy matrix, and it is one of the principal renewable energy sources. According to the 2020 "Infowind" report of the Brazilian Wind Energy Association (ABEEólica) (2020), Brazil's wind power generation has 15.6 Gigawatts (GW) of installed capacity with 624 wind farms in March 2020. In 2019, 55.9 Terawatt-hours (TWh) of wind energy were generated, recording a growth of 15.5% in relation to the previous year. This generation supplies 88.5 million inhabitants and represents 17% of the energy consumed in National Interconnected System.

Furthermore, wind speed is characterized by its high level of uncertainty and nonlinear behavior. Due to these behaviors, coupled with the lack of forecasting mathematical tools to provide coherent predictions, wind energy is classified as an intermittent source, i.e., the supply of wind energy is unstable. This erratic behavior makes to predict wind energy in an accurately way a challenge (Liu and Chen, 2019; Moreno *et al.*, 2019).

Despite the increasing wind power production and wind farm's installed capacity in Brazil, the energy market and operation's rules given by National Electrical System Operator (ONS) still not represent in an accurate way the wind energy, resulting in a big impact to investors and power system operations, mostly due to lots of wind farm curtailments imposed by load flow constrain-off (Ribeiro *et al.*, 2019).

Due to the wind characteristics and the current Brazilian electrical system's scenario, forecasting wind energy as accurate as possible has great importance to the energy's market and ONS. Hence, the objective of this paper is to propose a forecasting framework combining Variational Mode Decomposition (VMD) with Machine Learning forecasting models. The model will be applied to train the intrinsic mode functions (IMFs) generated by the decomposition step aiming to forecasting the wind power generation in a multi-step-ahead forecasting strategy (30 minutes, 1 hour, and 2 hours ahead). Each dataset output was decomposed into five different IMFs by VMD. The training process was performed by Bayesian Regularization of Artificial Neural Networks (BRNN), Cubist Regression (CUBIST), and Support Vector Regression (SVR) with Radial Basis Function kernel, respectively, applied into each component. The components predictions are summed giving three different predictions, one for each model, named as VMD–BRNN, VMD–CUBIST, and VMD–SVR, respectively.

The main contributions of this paper can be summarized as follows:

i) The first contribution is related to evaluate the use of signal decomposition method for wind energy forecasting.

ii) As the second contribution, we can highlight the use of exogenous input signals coupled with past (delayed) wind power observations (input lags), to provide additional information to the model.

iii) Last, this paper evaluates the proposed framework forecasting in a multi-step-ahead forecasting strategy (30 minutes, 1 hour, and 2 hours ahead).

The remainder of this paper is organized as follows: In Section 2.1 a brief description of the dataset adopted in this paper is presented. The forecasting models applied in this study are described in Section 2.2. Section 3 details the procedures applied in the research methodology. Results obtained and related discussion about models' forecasting performance are mentioned in Section 4. Finally, Section 5 concludes this study with considerations and some directions for future research proposals.

2. MATERIAL AND METHODS

This section presents the description of the material analyzed as well the models' definition applied in this paper.

2.1 Datasets description

The collected datasets refer to the wind turbine power generation sampled at 10 minutes basis. All variables were related to a wind farm located at Parazinho city, RN (Rio Grande do Norte state) - Brazil. The measurement period comprises the days 23, 24, and 26 of August 2017. For each day, the time series length reached 144 samples, with 10 minutes sampling rate.

The common approach on the wind energy forecasting is consider only wind speed as input to predict the next power production on the desired number of steps-ahead. However, the actual wind turbine generator (WTG) operation condition introduces some effects on the next step of power production, and it can be represented into the forecasting modeling as exogenous variables. As an example, the absolute wind direction and nacelle direction are two important variables that affect the power production, especially in scenarios where wind sector management control (WSM) could be activated to avoid dangerous turbulence effects on WTG's blade, gearbox, bearings, among others. Usually, WSM acts as an active constrain diminishing the overall production on a certain absolute wind direction relative to the nacelle direction, as a result of the wake effect introduced by the wind farm or WTG located nearby. To map this effect on power forecasting, we also have considered as input the set of variables related to this condition. Figure 1 shows the inside vision of a wind turbine, and its components. Table 1 presents the output and inputs of the system, and their respectively unit measures.

Table 1. Output and inputs of the system

Type	Description	Unit Measure
Output	Power	kW
Input	Generator Bearing Temperature	Celsius
Input	Generator Bearing 2 Temperature	Celsius
Input	Generator Speed	RPM
Input	Wind Speed	m/s
Input	Absolute Wind Direction	Degrees
Input	Nacelle Direction	Degrees
Input	Ambient Temperature	Celsius

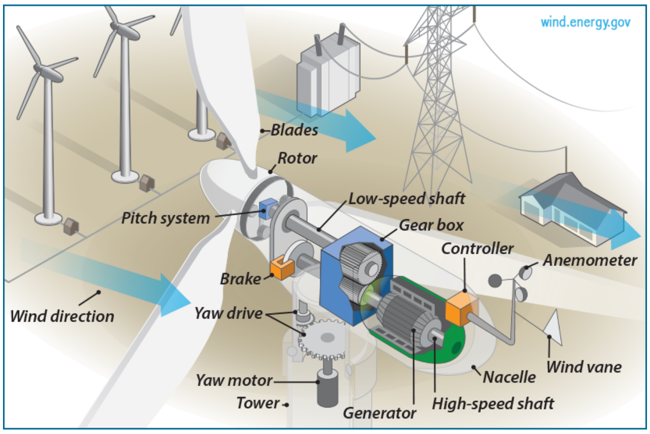

Figure 1. The inside of a wind turbine (United States Secretary of Energy, 2020)

Further, each dataset was split into training and test sets in the proportion of 70 and 30%, respectively. These proportions allow the models to learn the data pattern and behavior by using a adequate number of observations, as well as to make it possible to evaluate the learning in a sufficient number of values. The three datasets are illustrated in Fig. 2 and named as datasets 1, 2 and 3, respectively.

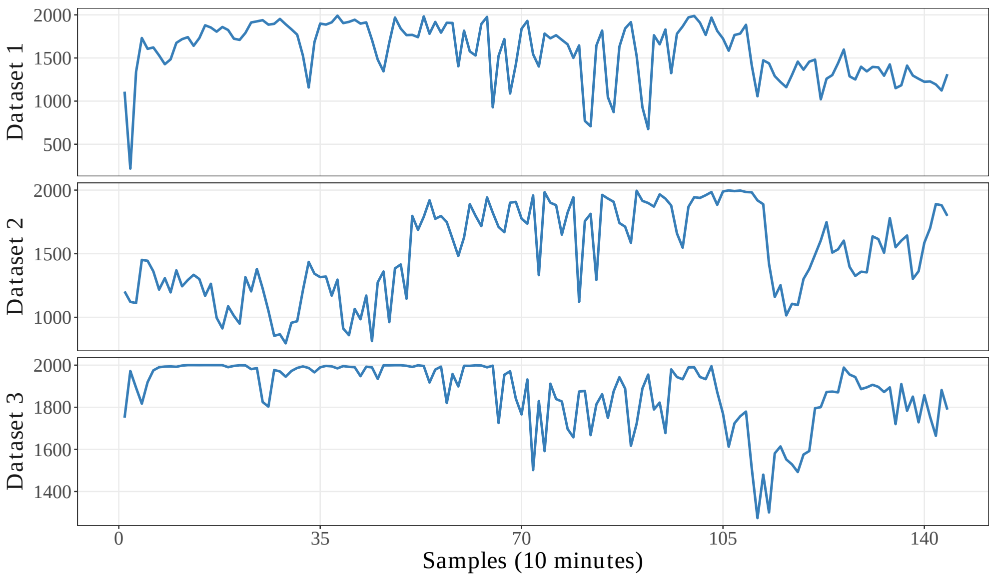

Figure 2. Datasets for August 23rd, 24th, and 26th, 2017

2.2 Methods

This section presents the main aspects of the methods proposed in this paper. The VMD method is presented followed by the description of the evaluated forecasting models.

2.2.1 Bayesian Regularization of Artificial Neural Networks

BRNN is a kind of feedforward artificial neural network, a two-layer neural network, composed by one input and one hidden layer, which uses the Bayesian methods, such as empirical Bayes, for parameter estimation, to avoid overfitting (MacKay, 1992). In the BRNN formulation, the variances are regularization parameters, in which the trade-off between goodness-of-fit and smoothing can be controlled. Also, in this approach the method of Nguyen and Widrow (1990) is used to assign initial weights of neural network and the Gauss-Newton training algorithm to perform the optimization.

2.2.2 Cubist Regression

CUBIST is a rule-based algorithm used to build forecasting models (in the time series field) based on the analysis of input data (Quinlan, 1992). It estimates the target values by establishing regression models with one or more rules (committee/ensemble of rules) based on the input set. These rules are employed based on a combination of conditions with a linear function (in general linear regression). When the rule satisfies all conditions defined in the learning process, this approach can execute multiple rules once and find different linear functions suitable to forecast wind energy. However, if the standard deviation reduction value is smaller or equal to the expected error for sub-tree, some leaves are pruned to avoid overfitting (Ribeiro *et al.*, 2020).

2.2.3 Support Vector Regression

SVR is a type support vector machine that consists in determining support vectors close to a hyperplane, which maximizes the margin between two-point classes obtained from the difference between the target value and a threshold. To deal with non-linear problems SVR takes into account kernel functions, which calculates the similarity between two observations through the inner product. In this paper, the radial basis function kernel is adopted. The main advantages of the use of SVR lie in its capacity to capture the predictor non-linearity and then use it to improve the forecasting cases (Drucker *et al.*, 1997; da Silva *et al.*, 2020b).

2.2.4 Variational Mode Decomposition

VMD is a pre-processing technique in the field of decomposition approaches, which decomposes a time series into a finite and predefined k number of Intrinsic Mode Functions (IMF) or mode functions. In a general way, VMD reproduces the decomposed signal with different sparsity properties (Dragomiretskiy and Zosso, 2013). There are three main concepts related to VMD, which are Wiener filtering, Hilbert transform and analytic signal, and frequency mixing and heterodyne demodulation. Sparsity prior of each mode is chosen as bandwidth in the spectral domain and can be accessed by the following scheme for each model: (i) compute associated analytic signal utilizing the Hilbert transform to obtain a unilateral frequency spectrum; (ii) shift frequency spectrum of mode to baseband by mixing the exponential tune to the respective estimated center frequency; and (iii) the bandwidth estimated through the Gaussian smoothness of the demodulated signal (Moreno *et al.*, 2020).

3. METHODOLOGY

This section describes the main steps in the data analysis adopted by BRNN, CUBIST, SVR, and VMD based forecasting models.

Step 1: First, the dataset output variables are decomposed into five IMFs by performing VMD, as presented in Fig. 3. The lag equals 2 was chosen by grid-search, applied on the IMFs creating two inputs from the lags, and applied on the exogenous inputs as well. Further, the new data is split into training and test sets. The test set consists of the last 42 observations, corresponding 30% of the dataset, and the training set defined by the remaining samples. In the training state, leave one-out-cross-validation with time slice was adopted, such as developed by Ribeiro and Coelho (2020).

Step 2: Each IMF is trained with each model described in Section 2.2 using time-slice validation approach. Next, the IMF predictions were reconstructed by a simple summation-grouping model, in other words, the IMF is trained by the same model and is summed. Then, three predictions outputs were generated named VMD–BRNN, VMD–CUBIST, and VMD–SVR.

Step 3: A recursive strategy is employed to develop multi-step-ahead wind energy generation forecasting (Moreno *et al.*, 2020). Regarding this, one model is fitted for one-step-ahead forecasting, then the recursive strategy uses this forecasting result as an input for the same model to forecast the next step, continuing until the desirable forecasting horizon. In this study, the aim is to obtain the cases up to H next steps, especially up to 3 (30 minutes ahead), 6 (1 hour ahead), and 12-steps-ahead (2 hours ahead), respectively. The following structures are considered,

$$\hat{y}_{(t+h)} = \begin{cases} \hat{f}\left\{\hat{y}_{(t+h-1)},\, \hat{y}_{(t+h-2)},\, \mathbf{X}_{(t+h-3)}\right\} & \text{if } h = 3, \\ \hat{f}\left\{\hat{y}_{(t+h-1)},\, \hat{y}_{(t+h-2)},\, \mathbf{X}_{(t+h-6)}\right\} & \text{if } h = 6, \\ \hat{f}\left\{\hat{y}_{(t+h-1)},\, \hat{y}_{(t+h-2)},\, \mathbf{X}_{(t+h-12)}\right\} & \text{if } h = 12, \end{cases} \tag{1}$$

where $\hat{f}$ is a function that maps the wind energy generation, $\hat{y}_{(t+h)}$ is the forecast of wind energy in horizon h =3, 6 and 12, $y_{(t+h-1)}$, $y_{(t+h-2)}$ are the previous observed, $\hat{y}_{(t+h-1)}$, $\hat{y}_{(t+h-2)}$ are the predicted wind energy, $\mathbf{X}_{(t+h-n_x)}$ is the exogenous inputs vector at the maximum lag of inputs ($n_x = 3$ if $h = 3$, $n_x = 6$ if $h = 6$, and $n_x = 12$ if $h = 12$). The analyses are developed using `{caret}` package (Kuhn, 2020) in `R` software (R Core Team, 2020).

Step 4: To evaluate the effectiveness of adopted models, from obtained forecasts out-of-sample (test set), improvement percentage (IP) index, relative root mean square error (RRMSE), and symmetric mean absolute percentage error (sMAPE) performance criteria, in Eq. (2), (3), and (4), respectively, are computed as

$$\text{IP} = \quad 100 \times \frac{M_c - M_b}{M_c}, \tag{2}$$

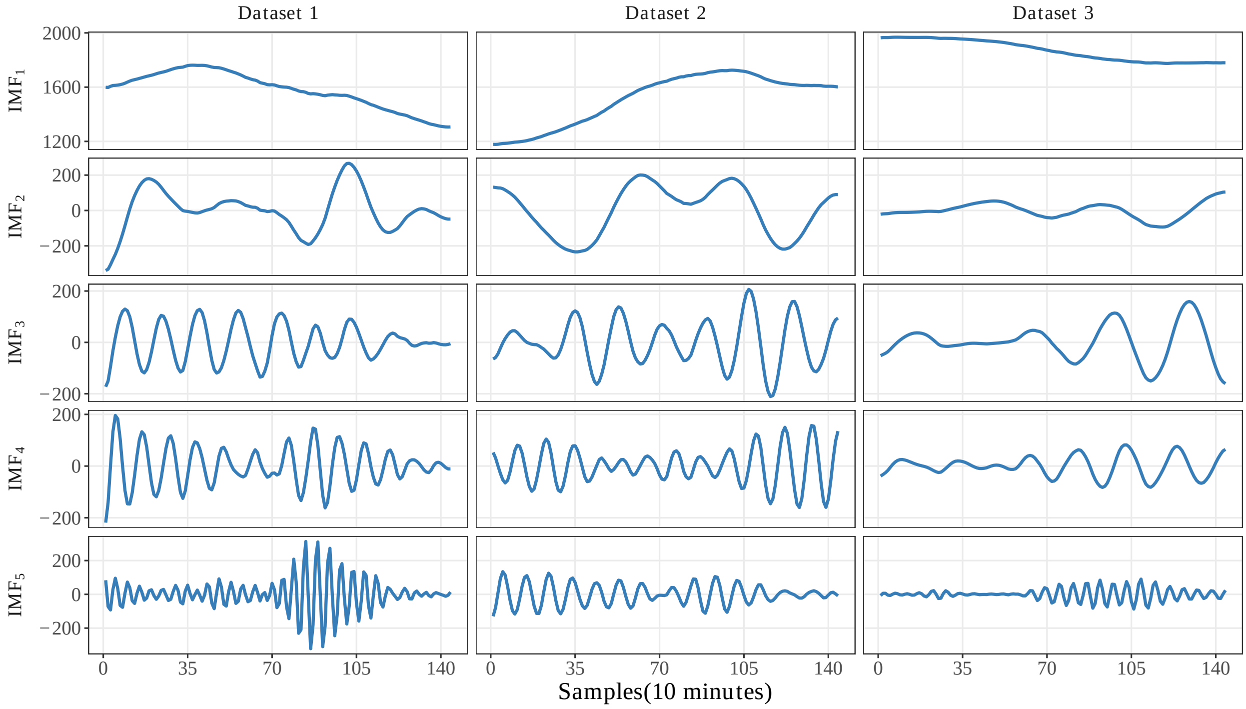

Figure 3. Datasets decomposed into IMFs by VMD approach

$$\text{RRMSE} = \frac{\sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}}{\frac{1}{n}\sum_{i=1}^{n} y_i}, \tag{3}$$

$$\text{sMAPE} = \frac{2}{n}\sum_{i=1}^{n}\frac{|y_i - \hat{y}_i|}{|y_i| + |\hat{y}_i|}, \tag{4}$$

where n is the number of observation, y_i and $\hat{y}_i$ are the i-th observed and predicted values, respectively. Also, the M_c and M_b represent the performance measure of compared and best models, respectively.

The proposed model framework as described in this Section is illustrated in Figure 4.

4. RESULTS AND DISCUSSIONS

This section describes the main results obtained by the proposed framework forecasting model for wind energy multi-step-ahead forecasting. The performance metrics of the proposed and compared models are presented in Tab. 2 for all three datasets, in all forecasting horizons (three, six and twelve-steps ahead), and all performance criteria. The best performance accuracy is highlighted in bold. The experiment compared the decomposed and non-decomposed models' performance. In all cases, VMD–CUBIST model outperformed the VMD and single models for both performance criteria.

Regarding the dataset 1, the performance metric improvement of VMD–CUBIST model ranged between 14.80% - 74.75%, where the SVR model presented the worse performance in all forecasting horizons for both performance criteria, and VMD–BRNN model presented the smaller difference from the VMD–CUBIST performance results. For dataset 2 the performance improvement of VMD–CUBIST model ranged between 3.00% - 68.87%, where the BRNN model presented the worse performance in all forecasting horizons for both performance criteria, and VMD–BRNN model presented the smaller difference from the VMD–CUBIST performance results in forecasting 30 minutes and 1 hour ahead, and SVR in forecasting 2 hours ahead. And, for dataset 3 the performance improvement of VMD–CUBIST model ranged between 4.44% - 83.30%, where the BRNN model presented the worse performance in all forecasting horizons for both performance criteria, and VMD–BRNN model presented the smaller difference from the VMD–CUBIST performance results in forecasting 30 minutes, and VMD–SVR in forecasting 1 and 2 hours ahead.

These results are due to the VMD approach, which deals with the non-linearity and non-stationarity behaviors of the wind power generation data, and completely neutralizes the residual noise producing an improved method (da Silva *et al.*, 2020b; Moreno *et al.*, 2020). In addition, CUBIST model has been effective dealing with the non-stationarity behavior of

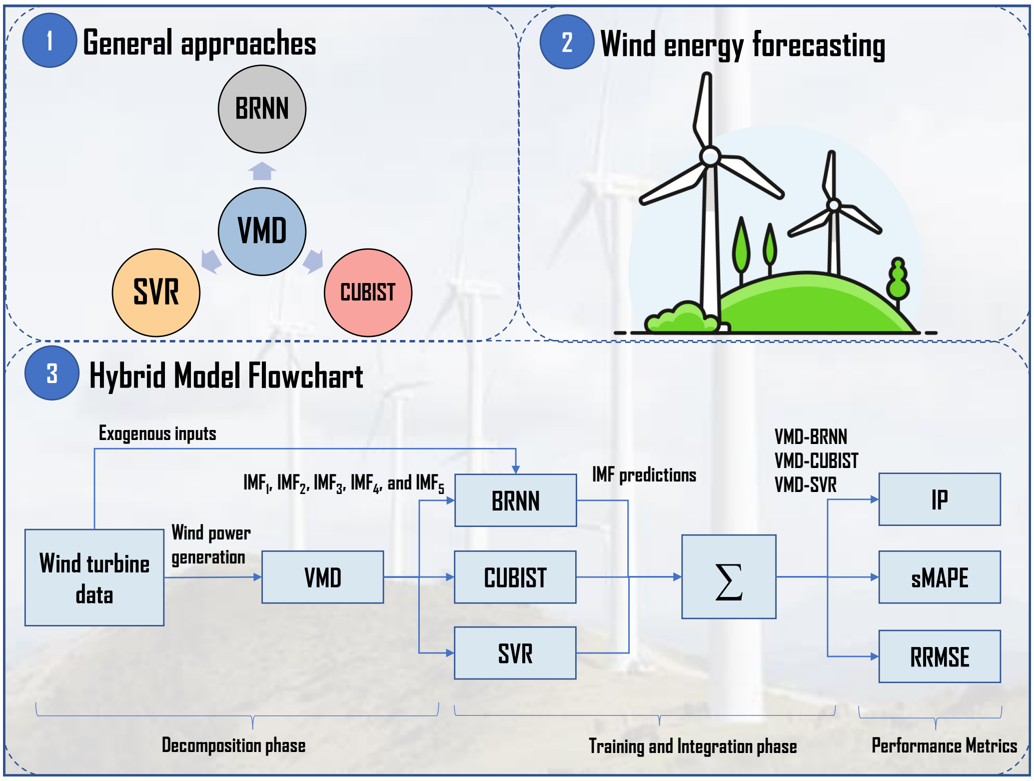

Figure 4. Wind energy forecasting diagram

Table 2. Performance measures of the single and decomposed models

Dataset	Forecasting Horizon	Criteria	Model					
			BRNN	CUBIST	SVR	VMD–BRNN	VMD–CUBIST	VMD–SVR
1	Three-steps	RRMSE	21.96%	17.60%	22.01%	8.63%	**7.35%**	18.08%
		sMAPE	22.03%	16.70%	23.22%	7.39%	**5.86%**	18.13%
	Six-steps	RRMSE	20.94%	17.60%	22.25%	13.07%	**8.70%**	18.44%
		sMAPE	20.47%	16.70%	23.61%	11.51%	**6.57%**	18.46%
	Twelve-steps	RRMSE	20.56%	17.60%	22.28%	17.65%	**10.53%**	18.72%
		sMAPE	19.94%	16.70%	23.63%	15.35%	**7.79%**	18.76%
2	Three-steps	RRMSE	17.17%	14.38%	10.84%	5.51%	**5.34%**	8.78%
		sMAPE	12.89%	11.08%	9.18%	4.81%	**4.51%**	6.59%
	Six-steps	RRMSE	17.55%	14.38%	11.00%	8.07%	**7.51%**	12.72%
		sMAPE	13.22%	11.08%	9.21%	6.89%	**6.39%**	10.21%
	Twelve-steps	RRMSE	17.85%	14.38%	11.02%	12.60%	**9.20%**	13.19%
		sMAPE	13.34%	11.08%	9.25%	10.32%	**7.59%**	10.79%
3	Three-steps	RRMSE	17.71%	4.56%	7.11%	3.09%	**2.96%**	5.35%
		sMAPE	14.01%	3.59%	5.20%	2.48%	**2.34%**	4.84%
	Six-steps	RRMSE	15.57%	8.73%	7.40%	5.55%	**3.16%**	5.18%
		sMAPE	12.20%	7.87%	5.43%	4.48%	**2.45%**	4.70%
	Twelve-steps	RRMSE	14.84%	10.15%	7.39%	7.79%	**4.04%**	5.13%
		sMAPE	11.79%	8.22%	5.43%	6.13%	**3.16%**	4.67%

unstable signals (da Silva *et al.*, 2020a; Ribeiro *et al.*, 2020), due to the the ensemble of rules based on a combination of conditions with a linear function that the algorithm performs. The combination of the strengths of both approaches made it possible to outperform the VMD models, and specially, the single models.

Therefore, based on the performance criteria analysis VMD–CUBIST model is the most accurate model for the given datasets in all forecasting horizons. Figures 5, 6, and 7 present the observed time-series (blue line) versus the versus the predictions given by the proposed model (red line), for dataset 1, 2, and 3, respectively.

In all datasets it is possible to notice that in all forecasting horizons the VMD–CUBIST model could learn accurately the pattern and behavior of the data in both training and test sets, allowing to predict accurate values compatible with the observed time-series.

Also, it is important to highlight that, even though the proposed model presented difficulties to follow the extremes of the data variability, the results indicate that the model is capable of predicting accurate values for wind power generation for different datasets in different forecasting horizons.

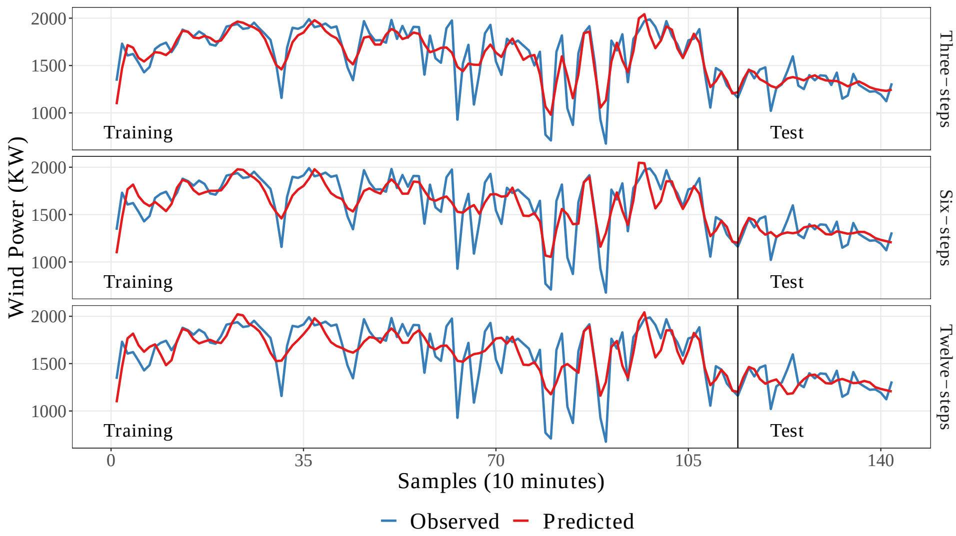

Figure 5. Observed versus predicted values for Dataset 1 in all forecasting horizons

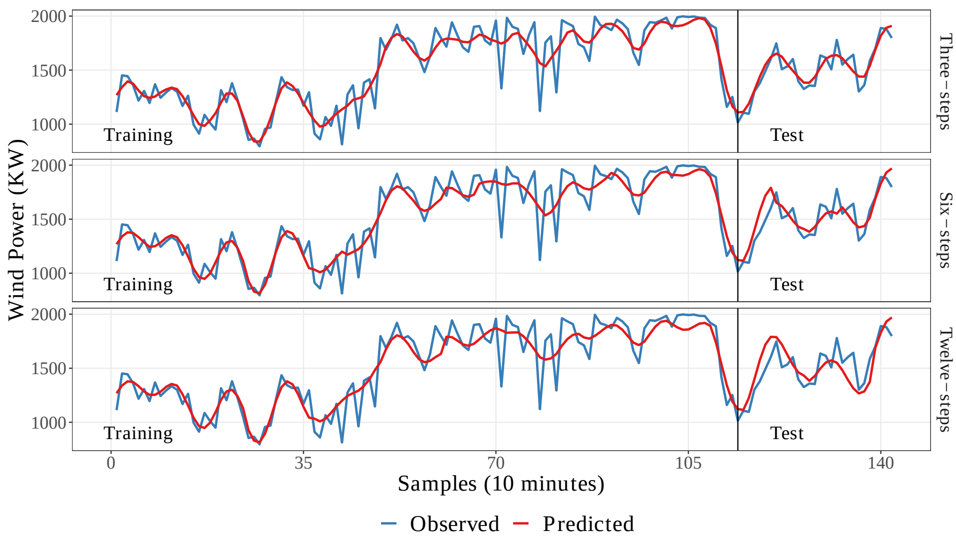

Figure 6. Observed versus predicted values for Dataset 2 in all forecasting horizons

5. CONCLUSION AND FUTURE RESEARCH

In this paper, machine learning approaches named BRNN, CUBIST, and SVR, as well as VMD approach, were employed in the task of forecasting three (30 minutes), six (1 hour), and twelve (2 hours) steps-ahead the wind energy of a wind turbine in a farm located at Parazinho city, Brazil. VMD approach decomposed the wind energy generation data into five components. Each component was trained and fitted with three well-known machine learning model. The predictions of the components were grouped by trained models and summed to generate three models. The IP, RRMSE, and sMAPE criteria were adopted to evaluate the performance of the compared approaches.

The results show that the VMD–CUBIST can accurately forecast wind energy generation. The proposed VMD–CUBIST model outperformed single model approach and other VMD models in the terms of RRMSE and sMAPE performance criteria. Even in large forecasting windows, i.e., forecasting 2 hours ahead, the maximum error signal reached by VMD–CUBIST was 10.53%, showing that the approach is promising for forecasting wind energy multi-step ahead.

For future works, it is intended to adopt (i) stacking ensemble learning approach, (ii) different signal decomposition approaches, and (iii) multi-objective optimization approach to tune hyperparameters of forecasting models.

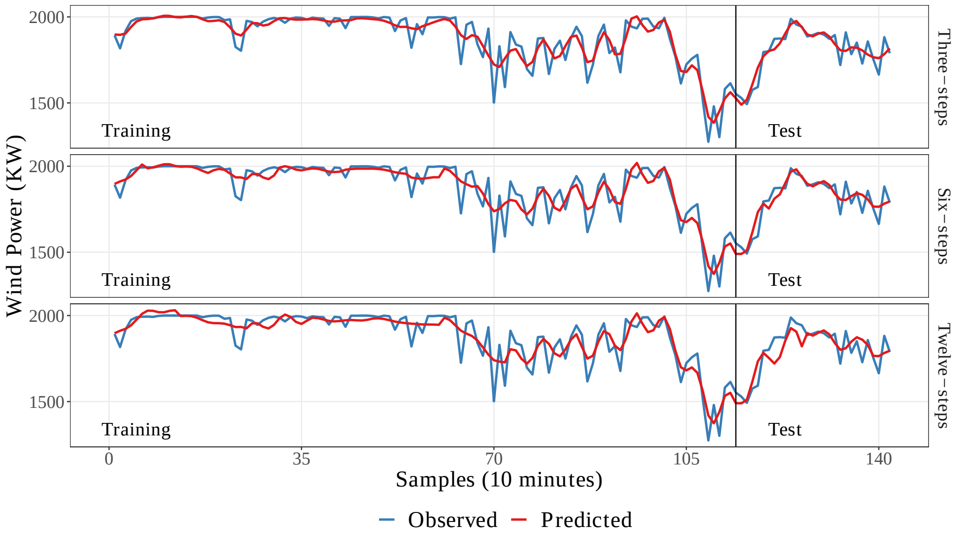

Figure 7. Observed versus predicted values for Dataset 3 in all forecasting horizons

6. ACKNOWLEDGEMENTS

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