COBEM 2021 Florianópolis - Brasil
ABCM Associação Brasileira de Engenharia e Ciências Mecânicas
26th ABCM International Congress of Mechanical Engineering
November 22-26, 2021. Florianópolis, SC, Brazil

COB-2021-0022
MULTI-STEP WIND SPEED FORECASTING BASED ON MULTI-STAGE DECOMPOSITION APPROACH

Ramon Gomes da Silva[1]
gomes.ramon@pucpr.edu.br
Sinvaldo Rodrigues Moreno[2]
sinvaldo.moreno@gmail.com
Matheus Henrique Dal Molin Ribeiro[1,3]
mribeiro@utfpr.edu.br
Viviana Cocco Mariani[2,4]
viviana.mariani@pucpr.br
Leandro dos Santos Coelho[1,4]
leandro.coelho@pucpr.br

[1] Industrial and Systems Engineering Graduate Program (PPGEPS), Pontifical Catholic University of Parana (PUCPR). 1155, Rua Imaculada Conceição, Curitiba, PR, Brazil. 80215-901
[2] Mechanical Engineering Graduate Program (PPGEM), Pontifical Catholic University of Parana (PUCPR). 1155, Rua Imaculada Conceição, Curitiba, PR, Brazil. 80215-901
[3] Department of Mathematics, Federal University of Technology - Parana (UTFPR). Via do Conhecimento, KM 01 - Fraron, Pato Branco, PR, Brazil. 85503-390
[4] Department of Electrical Engineering, Federal University of Parana (UFPR). 100, Avenida Coronel Francisco Heraclito dos Santos, Curitiba, PR, Brazil. 81530-000

Abstract. *Wind energy is one of the sources which is 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 speed with high accuracy is a challenging task. The contribution of this study proposes a framework that combines Singular Spectrum Analysis (SSA) and Variational Mode Decomposition (VMD) based on Machine Learning models to forecast the wind speed of a turbine in a wind farm at Parazinho city, Brazil, using a multi-step ahead forecasting strategy (10, 30, and 60 minutes ahead). The forecasting models of the wind speed time series are k-Nearest Neighbor and Support Vector Regression. The performance of the proposed forecasting models were evaluated by using mean absolute percentage error and root mean square error criteria. The VMD–SSA models outperform the SSA, VMD, and single models in all evaluated forecasting horizons, with a performance improvement that ranges within 0.20%–55.78%. Indeed, VMD–SSA is an efficient and accurate model for wind speed forecasting.*

Keywords: *Wind speed, time series forecasting, singular spectrum analysis, 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 of hydroelectric systems (57.8% of the energy production), 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 2021 “INFOVENTO” report of the Brazilian Wind Energy Association (ABEEólica) (2021), Brazil is currently in 7th place in the world ranking of installed wind energy capacity, with 18 Gigawatts (GW) of installed capacity coming from the more than 8,300 generators in operation, distributed in the 695 wind farms spread along the coast of the country, as of February 2021. In 2019, 55.9 Terawatt-hours (TWh) of wind energy were generated, recording a growth of 15.5% concerning the previous year. This generation supplies 88.5 million inhabitants and represents 17% of the energy consumed in the 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 speed in an accurate way a challenging task (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 the National Electrical System Operator (ONS) still not represent in an accurate way the wind energy, resulting in a big impact on investors and power system operations, mostly due to lots of wind farm curtailments imposed by load flow constrain-off (da Silva *et al.*, 2020b).

Due to the wind characteristics and the current Brazilian electrical system's scenario, forecasting wind speed as accurately as possible has great importance to the energy market and ONS. Hence, the objective of this study is to propose a forecasting framework combining Singular Spectrum Analysis (SSA) and Variational Mode Decomposition (VMD) with Machine Learning forecasting models. The model will be applied to train the components generated by the decomposition step aiming to forecast the wind speed in a multi-step ahead forecasting strategy (10, 30, and 60 minutes ahead). The model proposed in this study has two stages, previously is made the decomposition with VMD, and after application of SSA. VMD extracts the trend components from each original dataset output, and the remaining signal is decomposed into 4 other components by SSA, i.e., each dataset output is decomposed into five different components by VMD and SSA. The training process was performed k-Nearest Neighbor (KNN) and Support Vector Regression (SVR) with linear kernel, respectively, applied into each component. The components predictions are summed giving two different predictions, one for each model, named as VMD–SSA–KNN and VMD–SSA–SVR, respectively. The models' performance are evaluated by using improvement performance index (IP), mean absolute percentage error (MAPE), and root mean square error (RMSE) performance criteria.

The main contributions of this study can be summarized as follows: (i) The first contribution is related to evaluating the use of a multi-stage signal decomposition approach for wind speed forecasting. (ii) Second, the use of different machine learning forecasting models combined with the multi-stage signal decomposition. (iii) Last, this study evaluates the proposed framework forecasting in a multi-step ahead forecasting strategy (10, 30, and 60 minutes ahead) for wind speed time series.

The rest of this paper is structured as follows. Section 2 describes the dataset employed for analysis. Section 3 defines the models designed and evaluated. Section 4 details the procedures of the proposed model framework. After, Section 5 presents the results obtained and discussions. Finally, Section 6 concludes with the final considerations and future works.

2. DATASET DESCRIPTION

The set of time series applied as input signal consists of three consecutive months of wind speed measured every 10 min at 95 m at the level of the ground, from a wind generator with blade diameter of 100 m. These measurements came from a monitoring wind speed for a large wind farm, with approximately 150 Megawatts (MW) of installed capacity, located in the State of Rio Grande do Norte, Northeast region of Brazil, more specifically at Parazinho city. Figure 1 shows the inside vision of a wind turbine and its components. The period of measurement comprises the months of March, April, and May 2020. The length of the time series reached 4,464 samples for March and May 2020, and 4,320 samples for April 2020, with a sampling rate of 10 min, as presented in Fig. 2.

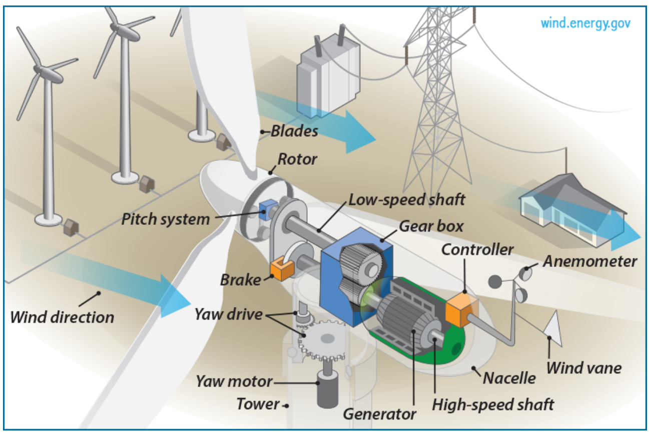

Figure 1. The inside of a wind turbine (United States Secretary of Energy, 2021)

3. METHODS

This section presents the main aspects of the methods proposed in this study. The SSA and VMD methods are presented followed by the description of the evaluated forecasting models.

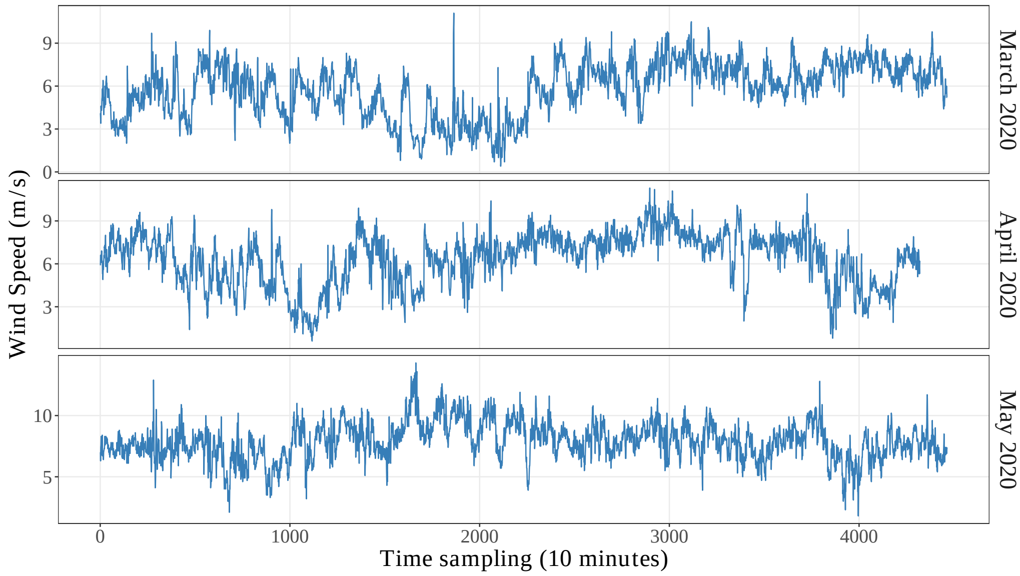

Figure 2. Datasets for March, April, and May 2020, respectively.

3.1 Singular Spectrum Analysis

There are four steps in the SSA algorithm, to simplify it can be summarized into two groups: decomposition and reconstruction. The embedding and singular value decomposition (SVD) steps belong to data decomposition, while the grouping and diagonal averaging belong to data reconstruction. An overview of each step is presented as follows: (i) **Embedding step**: the one-dimensional time series is represented as a multidimensional series whose dimension is called the window length that forms the trajectory matrix. The parameters of this step are the window length, L, usually with a value of $L < \frac{N}{2}$, and the time series length; (ii) **SVD step**: the singular N value decomposition of the trajectory matrix into a sum of rank-one bi-orthogonal matrices; (iii) **Grouping step**: the splitting of the matrices, computed at the SVD step, into several groups and added within each group. The result of the step is a representation of the trajectory matrix as a sum of several resultant matrices; and (iv) **Diagonal averaging step**: It is a linear operation known as diagonal averaging or de-*hankelization*, where each elementary matrix X_K is transformed into a principal component of length N. This way, we obtain a decomposition of the initial series into several additive components $X^{(k)} = \left(x_1^{(k)}, \ldots, x_N^{(k)}\right)$. The detailed steps of SSA can be found in (Golyandina *et al.*, 2001; Moreno and Coelho, 2018; Moreno *et al.*, 2020).

3.2 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 (i) Wiener filtering, (ii) Hilbert transform and analytic signal, and (iii) 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. Since VMD acts as a non-recursive method, it requires that the sum of estimate bandwidth of each intrinsic mode function component be the lowest. (Moreno *et al.*, 2020).

3.3 *k*-Nearest Neighbor

KNN is an instance-based learner model designed by Fix and Hodges (1951) to solve classification but generalized for regression by Altman (1992). In fact, in the time series context, the KNN searches k nearest past similar values in the input set, in which these k values are namely nearest neighbors. In this context, to find the nearest values, a similarity measure is adopted. The k-nearest neighbors are those that similarity measures between past values and new values are the smallest. Considering that the set of k-nearest neighbors are defined, the forecasting of wind speed is obtained through an average of past similar values. In contrast to the simplicity of this supervised learning, the computational cost may be a disadvantage (Ribeiro and Coelho, 2020).

3.4 Support Vector Regression

SVR is a type of support vector machine (SVM) focusing in regression problems, once SVM was designed for classification problems. SVR consists of 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 study, the linear 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.*, 2020a).

4. PROPOSED MODEL FRAMEWORK

This section describes the main steps in the data analysis adopted by KNN, SVR, SSA, and VMD-based forecasting models. The proposed model framework is illustrated in Fig. 3 and further detailed as follows.

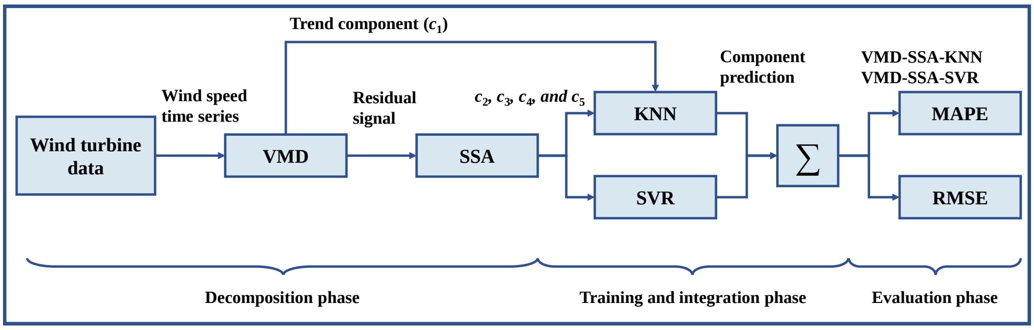

Figure 3. Proposed forecasting model framework

Step 1: First, VMD was performed to extract the trend component (c_1) from the original time series. The difference between the original time series and c_1 was calculated resulting in a high-frequency signal. This remaining signal was then decomposed by SSA into 4 other components (c_2 up to c_5). The 5 components are presented in Fig. 4. The lag equals to 5 was chosen by grid-search, applied on the components creating 5 lagged inputs. Further, the new data was split into training and test sets. The test set consists of the last 1,008 observations, corresponding to the last 7 days (around 22.5%) of the datasets, and the training set defined by the remaining samples. These proportions allow the models to learn the data pattern and behavior by using an adequate number of observations, as well as to make it possible to evaluate the learning in a sufficient number of values. In the training state, a 5-fold cross-validation was adopted, such as performed by Ribeiro *et al.* (2020) and da Silva *et al.* (2021).

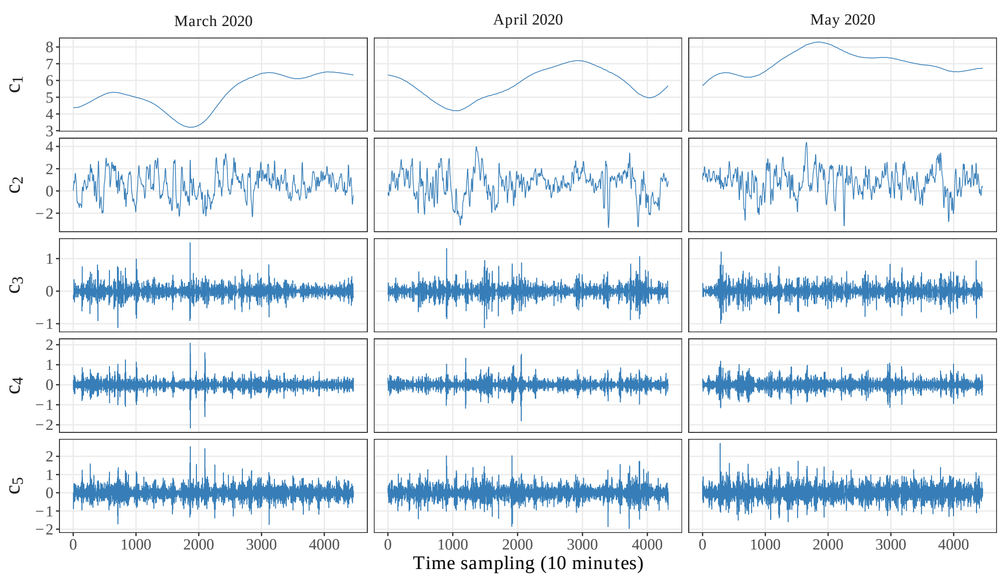

Figure 4. Datasets decomposed into components by VMD and SSA approaches

Step 2: Each component was trained with each model described in Section 3 using a 5-fold cross-validation approach. Next, the components predictions were reconstructed by a simple summation-grouping model, in other words, the component is trained by the same model and summed afterward. Then, two prediction outputs were generated named, VMD–SSA–KNN and VMD–SSA–SVR, respectively.

Step 3: A recursive strategy is employed to develop multi-step ahead wind speed forecasting (da Silva *et al.*, 2021). Regarding this, one model has 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. The recursive forecasting process always considers the forecast value on step $t+1$ to perform the next forecasting value on $t+2$, and so on, where t is the present time. As depicted in Fig. 5, where the forecast value is represented by a yellow color on step $t+1$, and for the forecasting of step $t+2$, the previous forecast value from the input vector and its representation become green. It can be seen that at the $t+5$ forecasting step will be remaining only one sample of real verified value and the following are past forecasts, and at $t+6$ forecasting step none sample of real verified value remains, only past forecast values are considered.

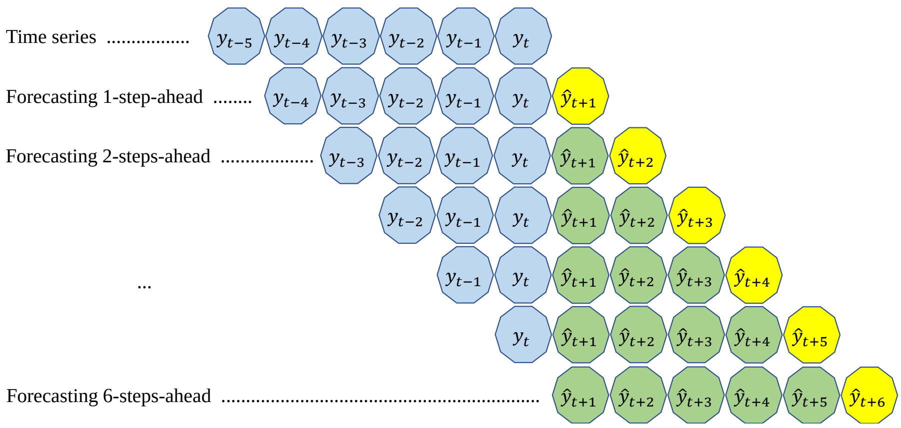

Figure 5. Recursive strategy of forecasting exemplified for 6-steps ahead.

In this study, the aim is to obtain the cases up to H next steps, especially up to 1 (10 minutes ahead), 3 (30 minutes ahead), and 6 (60 minutes ahead) steps ahead, respectively. The following structures are considered,

$$\hat{y}_{(t+h)} = \begin{cases} \hat{f}\left\{y_{(t+h-1)},\, y_{(t+h-2)},\, y_{(t+h-3)},\, y_{(t+h-4)},\, y_{(t+h-5)}\right\} & \text{if } h=1, \\ \hat{f}\left\{\hat{y}_{(t+h-1)},\, \hat{y}_{(t+h-2)},\, y_{(t+h-3)},\, y_{(t+h-4)},\, y_{(t+h-5)}\right\} & \text{if } h=3, \\ \hat{f}\left\{\hat{y}_{(t+h-1)},\, \hat{y}_{(t+h-2)},\, \hat{y}_{(t+h-3)},\, \hat{y}_{(t+h-4)},\, \hat{y}_{(t+h-5)}\right\} & \text{if } h=6, \end{cases} \tag{1}$$

where $\hat{f}$ is a function that maps the wind speed, $\hat{y}_{(t+h)}$ is the forecast of wind speed in time t in horizon h =1, 3, and 6, $y_{(t+h-1)}$ up to $y_{(t+h-5)}$ are the previous observed, $\hat{y}_{(t+h-1)}$ up to $\hat{y}_{(t+h-5)}$ are the predicted wind speed. The analyses are developed using the`{caret}` package developed by Kuhn (2020) in `R` software (R Core Team, 2020). The hyperparameters of the forecasting models were tuned by a grid-search.

Step 4: To evaluate the effectiveness of adopted models, from obtained forecasts out-of-sample (test set), IP, MAPE, and RMSE performance criteria, respectively, are computed as

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

$$\text{MAPE} = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{y_i - \hat{y}_i}{y_i}\right| \times 100, \tag{3}$$

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}, \tag{4}$$

where n is the number of observations (samples), 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 metric of compared and best models (which present the lowest MAPE and RMSE), respectively.

5. RESULTS AND DISCUSSIONS

This section describes the main results obtained by the proposed framework forecasting model for wind speed multi-step ahead forecasting. The performance metrics of the proposed and compared models are presented in Tab. 1 for all three datasets, in all forecasting horizons (10, 30, and 60 minutes ahead), and all performance criteria. The best performance accuracy of the model is highlighted in bold. The experiment compared the decomposed and non-decomposed models' performance. In all cases, the VMD–SSA model outperformed the SSA, VMD, and single models for all forecasting horizons in both performance criteria.

Table 1. Performance measures of the single and decomposed models

Dataset	Forecasting horizon	Criteria	VMD–SSA–KNN	VMD–SSA–SVR	SSA–KNN	SSA–SVR	VMD–KNN	VMD–SVR	KNN	SVR
March	10 minutes ahead	MAPE	**3.226%**	3.288%	4.050%	3.546%	5.195%	5.436%	5.750%	5.596%
		RMSE	0.2884	**0.2878**	0.3604	0.3171	0.4631	0.4739	0.5045	0.4936
	30 minutes ahead	MAPE	**3.483%**	3.628%	5.755%	5.630%	6.152%	6.363%	7.009%	6.846%
		RMSE	**0.3073**	0.3176	0.5220	0.5059	0.5464	0.5545	0.6045	0.5960
	60 minutes ahead	MAPE	**4.168%**	4.791%	6.374%	6.357%	6.607%	6.926%	8.262%	7.760%
		RMSE	**0.3724**	0.4226	0.5792	0.5657	0.5900	0.5974	0.7070	0.6688
April	10 minutes ahead	MAPE	5.355%	**4.657%**	7.128%	5.760%	8.447%	7.749%	8.871%	8.249%
		RMSE	0.3899	**0.3317**	0.5196	0.3800	0.6169	0.5731	0.6460	0.6066
	30 minutes ahead	MAPE	5.950%	**5.182%**	9.563%	8.851%	10.288%	9.843%	11.116%	10.778%
		RMSE	0.4373	**0.3664**	0.7143	0.6563	0.7628	0.7242	0.8287	0.7953
	60 minutes ahead	MAPE	7.290%	**6.893%**	10.741%	10.446%	11.290%	10.822%	12.626%	11.868%
		RMSE	0.5505	**0.4950**	0.8154	0.7833	0.8691	0.8228	0.9669	0.9328
May	10 minutes ahead	MAPE	4.129%	**3.713%**	5.197%	4.166%	6.907%	6.366%	7.009%	6.663%
		RMSE	0.3834	**0.3366**	0.4789	0.3739	0.6250	0.5716	0.6490	0.6035
	30 minutes ahead	MAPE	4.595%	**3.991%**	7.194%	6.809%	8.182%	7.545%	8.350%	8.116%
		RMSE	0.4270	**0.3595**	0.6676	0.6497	0.7427	0.6980	0.7979	0.7648
	60 minutes ahead	MAPE	5.770%	**4.874%**	8.255%	8.277%	9.108%	8.747%	10.237%	9.874%
		RMSE	0.5403	**0.4536**	0.7739	0.7780	0.8362	0.8077	0.9908	0.9344

Regarding the March dataset in 10 minutes ahead of forecasting, for the RMSE criterion, the performance metric improvement of VMD–SSA–SVR model ranged within 0.20%–42.94%, and for MAPE criterion the VMD–SSA–KNN model ranged within 1.89%–43.89%. For 30 and 60 minutes ahead, for both criteria, the VMD–SSA–KNN improved between 3.23%–50.30%. Regarding April and May datasets, for all forecasting horizons in both performance criteria, the VMD–SSA–SVR presented the better performance, with a performance improvement that ranged within 5.45%–55.78%. Further, the worst performance in all datasets for all forecasting horizons was presented by the KNN model with an average IP of 49.53%. The second better performance approach in all datasets and all forecasting horizons was the SSA–SVR approach with an average IP of 30.12%.

Calculating the average of the IP of each model made it possible to rank the models according to their performance compared to the most accurate model of each dataset in each forecasting horizon. It is presented the models ranked according to the average IP of all datasets in all forecasting horizons from the most to the least accurate model in Fig. 6. Also, the models are labeled as: (A) VMD–SSA–KNN, (B) VMD–SSA–SVR, (C) SSA–KNN, (D) SSA–SVR, (E) VMD–KNN, (F) VMD–SVR, (G) KNN, and (H) SVR. As analyzed in Tab. 1 and Fig. 6, the VMD–SSA–SVR and KNN are the most and least accurate models, respectively. Besides, we can notice that SVR-based models performed better than KNN-based models, regardless of the decomposition approach applied to the model. Among the decomposition approaches, models based on SSA performed better than models based on VMD. Indeed, it is evident that the combination of the two decomposition approaches performed better than the other approaches.

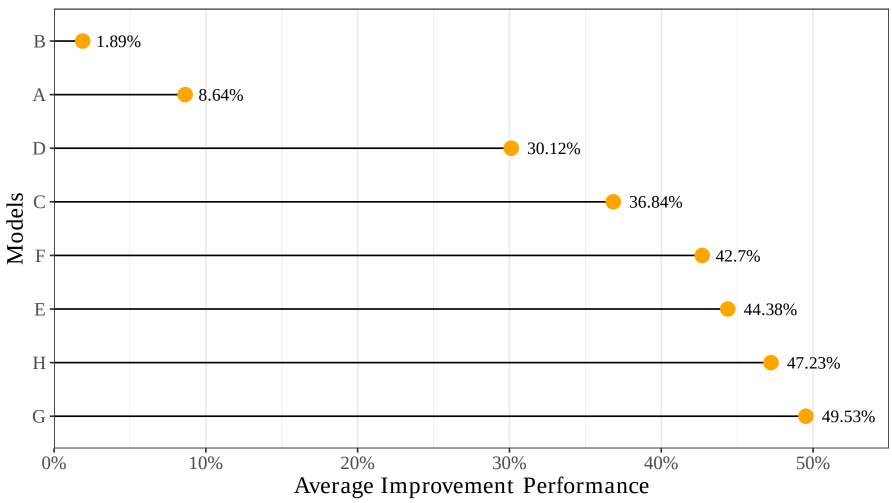

Figure 6. Average improvement performance of each model

These results are due to the VMD approach, which deals with the non-linearity and non-stationarity behaviors of the wind speed data, and completely neutralizes the residual noise-producing an improved method (da Silva *et al.*, 2020a), and due to the SSA approach, which is a powerful non-parametric method for processing non-stationary signals useful to filter the low-frequency noise (Moreno *et al.*, 2020). Besides, the SVR model has been effectively dealing with the non-linearity behavior of unstable signals, mostly due to kernel functions applied to it. The combination of the strengths of these approaches made it possible to outperform the SSA, VMD, and especially, the single models.

Therefore, based on the performance criteria analysis VMD–SSA approaches are the most accurate model for the given datasets in all forecasting horizons. Figure 7 presents the observed time series (blue line) versus the predictions given by the proposed model (red line) for the last 24 hours (144 observations) of the March, April, and May datasets, respectively.

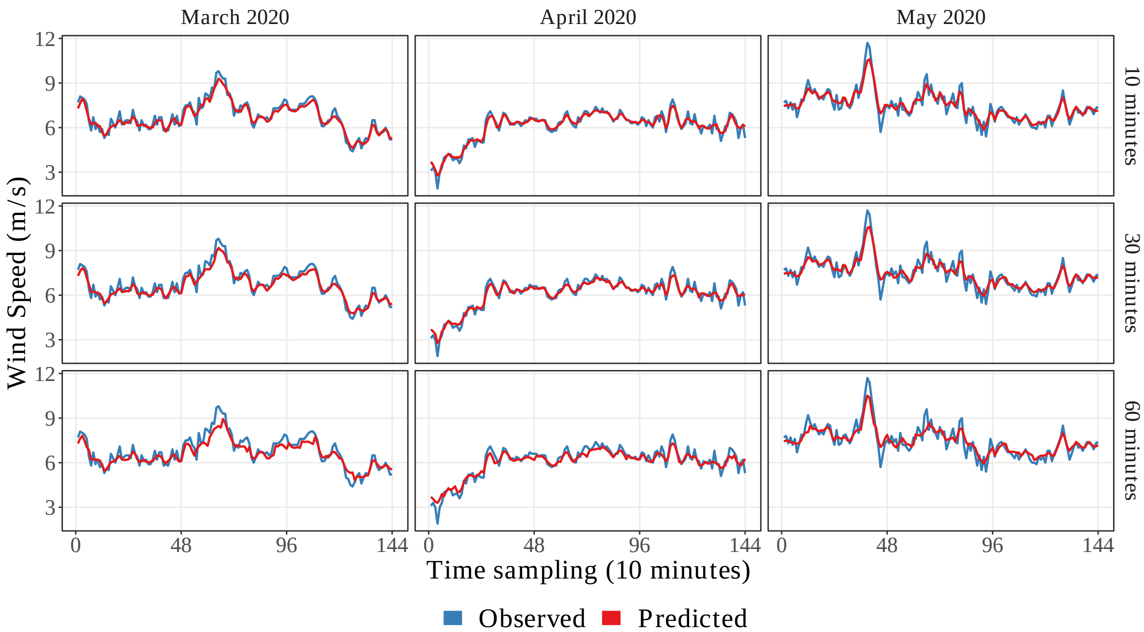

Figure 7. Observed versus predicted time series for the last 24 hours of all datasets in all forecasting horizons

In all datasets it is possible to notice that in all forecasting horizons the VMD–SSA approach 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.

6. CONCLUSION AND FUTURE RESEARCH

In this study, machine learning approaches named KNN and SVR, as well as SSA and VMD approaches were employed in the task of forecasting 10, 30, and 60 minutes ahead of the wind speed of a wind turbine in a farm located at Parazinho city, Brazil. VMD approach extracts the trend component from the wind speed data, and the remaining signal is decomposed into four components by the SSA approach. Each component was trained and fitted with two well-known machine learning models. The predictions of the components were grouped by trained models and summed to generate two models. The IP, MAPE, and RMSE criteria were adopted to evaluate the performance of the compared approaches.

The results show that the VMD–SSA approach can accurately forecast wind speed. The proposed VMD–SSA model outperformed single model, SSA, and VMD approaches in the terms of MAPE and RMSE performance criteria. Even in large forecasting windows, i.e., forecasting 60 minutes, the maximum error signal reached by VMD–SSA was 6.89% for the April dataset, showing that the approach is promising for forecasting wind energy multi-step ahead. Also, the ranking of the models according to the IP criterion, from the most to least accurate, is (B) VMD–SSA–SVR, (A) VMD–SSA–KNN, (D) SSA–SVR, (C) SSA–KNN, (F) VMD–SVR, (E) VMD–KNN, (H) SVR, and (G) KNN.

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

7. ACKNOWLEDGEMENTS

The authors would like to thank the National Council of Scientific and Technological Development of Brazil – CNPq (Grants number: 307958/2019-1-PQ, 307966/2019-4-PQ, 404659/2016-0-Univ, 405101/2016-3-Univ, 160817/2019-6-

PDJ), PRONEX '*Fundação Araucária*' 042/2018, and *Coordenação de Aperfeiçoamento de Pessoal de Nível Superior - Brasil* (CAPES) - Finance Code 001 for financial support of this work.

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