Short-range wind speed predictions in subtropical region using Artificial Intelligence

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ABSTRACT

Short-range wind speed predictions for subtropical region is performed by applying Artificial Neural Network (ANN) technique to the hourly time series representative of the site. To train the ANN and validate the technique, data for one year are collected by one tower, with anemometers installed at heights of 101.8, 81.8, 25.7, and 10.0 m. Different ANN configurations to Multilayer Perceptron (MLP), Recurrent Neural Network (RNN), Gated Recurrent Unit (GRU), and Long Short-Term Memory (LSTM), a deep learning algorithm based method, are applied for each site and height. A quantitative analysis is conducted and the statistical results are evaluated to select the configuration that best predicts the real data. These methods have lower computational costs than other techniques, such as numerical modelling. The proposed method is an important scientific contribution for reliable large-scale wind power forecasting and integration into existing grid systems in Uruguay. The best results of the short-term wind speed forecasting was for MLP, which performed the forecasts using a hybrid method based on recursive inference, followed by LSTM, at all the anemometer heights tested, suggesting that this method is a powerful tool that can help the *Administración Nacional de Usinas y Transmissiones Eléctricas* manage the national energy supply.

Keywords: Artificial Neural Networks, Computational Intelligence, Computational Modelling, Computer Science, Wind Energy and Wind Speed Forecasting.

1. INTRODUCTION

The integrity of natural systems is already a risk because of climate change caused by the intense emissions of greenhouse gases in the atmosphere. Currently, environmental pollution is a global issue that is receiving considerable attention, and alternative renewable resources to reduce pollution must be developed [1]. As a burgeoning type of renewable energy, wind energy has developed rapidly in the past decade [2,3]. [4] reported that wind power has the largest market share among renewable energy sources and is expected to maintain its rapid growth in the coming years. The country of Uruguay, which is in Latin America, surprisingly obtains 94% of its electricity from renewable sources [5]. Among the countries of the world, Uruguay ranks 4th in the generation of wind energy, according to the Renewables 2017 Global Status Report [6]. Wind speed forecasting is fundamental in the planning, controlling, and monitoring of intelligent wind power systems. However, owing to the stochastic and intermittent nature of wind, it is difficult to make satisfactory predictions [7]. Accurate short-term wind speed forecasting (1 to 12 h ahead) plays a substantial role in addressing this challenge. A correct forecast of the wind speed can reduce the risk of wind energy breaking in hybrid energy systems.

Regarding wind energy, the variability of the wind direction and speed throughout the day makes it difficult to decide whether to drive wind turbines, because in practice, wind exhibits temporal variations of several orders of magnitude, e.g. annual variations (owing to climatic changes), seasonal variations, daily variations (owing to the local microclimate), hourly variations (owing to land and sea breezes), and short-duration variations (bursts). Computational methods have been used to evaluate the wind behaviour and thus obtain valuable information for the electro-energy sector in several parts of the world and computational models can be useful for the identification of locations with high wind potential and, when used operationally in daily integrations, short-term energy generation forecasting [8]. The use of wind power generation for fuelling society and industries is very challenging for current power system operations. One reason for this is that wind power is an intermittent energy source with a high degree of randomness and instability [9]. ANN are among the most important soft computing methods, widely used for a great range of applications spanning across various scientific fields.

In [22], the short-term wind speed forecasting for Colonia Eulacio, Soriano Department, Uruguay, is performed by applying ANN technique to the hourly time series representative of the site.

The authors adopted a computational-intelligence model using a multilayer perceptron ANN with Levenberg–Marquardt Backpropagation. A multilayer perceptron is a class of feedforward artificial neural network. The ANN was trained to perform the forecasting of 1 hour ahead and then, using it, the trained network was applied to recursively infer the forecasting for the next hours of the wind speed. The results of the short-term wind speed forecasting showed good accuracy at all the anemometer heights tested, suggesting that the method is a powerful tool that can help the *Administración Nacional de Usinas y Trasmisiones Eléctricas (UTE)* manage the activities of generation, transmission, distribution and commercialization of electrical energy.

[25] show the estimate short-term wind speed forecasting 6 hours ahead (nowcasting) applying computational intelligence, by RNN, using anemometers data collected by an anemometric tower at a height of 100.0 m in Brazil (tropical region), and 101.8 m in Uruguay (subtropical region), both Latin American countries. The results of this study are compared with wind speed prediction results from the literature. In one of the cases investigated, this study proved to be more appropriate when analyzing evaluation metrics (error, and regression) of the prediction results obtained by the proposed model.

In [26], the short-range wind speed forecasting in the tropical region of Mucuri, Bahia, Brazil, applying the Artificial Neural Network (ANN) technique to the hourly time series representative of the site is presented. To perform the training, and validation of this technique, one month of data were collected in a tower with anemometers installed at heights of 100, 120, and 150 m. Different ANN configurations were applied to this site, and heights with aimed to define the most efficient ANN configuration, all of Multilayer Perceptrons with Levenberg-Marquardt Backpropagation training algorithm, to predict the wind speed for 1 hour ahead, and then apply it for 3, and 6 hours ahead. The mean R^2 and Pearson's r for wind speed forecasting for 1 hour ahead was 0.890, and 0.943, respectively. The statistical results showed that the application of the ANN technique to predict the wind speed at Bahia's site, and at higher heights presented good accuracy, attesting its ability to be used as a powerful tool in order to help the Brazil's National Electric System Operator (ONS) to improve the usage and integration of the wind energy into the national electrical grid.

[27] study the short-term wind speed forecasting in the tropical region of Mucuri, Bahia, Brazil, applying supervised machine learning algorithm by Multilayer Perceptron Neural Network, Recurrent Neural Network technique and Wavelet Packet Decomposition to the hourly time series representative of the site is presented. To train the Artificial Neural Network (ANN) and validate the technique, data for one month were collected by an anemometric tower at a height of 100.0 m. Different Wavelet families and different ANN configurations were applied for this site and height. Based on the outcomes of the study cases and results, it can be concluded that the proposed method (RNN + Meyer Wavelet level 3) performed the best results in the short-term forecasting horizon.

Therefore, the objective of this study was to identify the most efficient ANN configurations applying fully-connected RNN, GRU, and LSTM with Adam optimizer training algorithm for wind speed forecasting 1 hour ahead, and do a comparison with ANN MLP researched and developed in [22]. The Adam optimization algorithm is an extension to Stochastic Gradient Descent (SGD) that has recently seen broader adoption for deep learning applications in computer vision and natural language processing [23]. The algorithm was also applied for 3, 6, 9, and 12 h forecasts by using observational data collected from one tower, which was located in Colonia Eulacio, Soriano Department, Uruguay, as a reference. Anemometers were installed at heights of 101.8, 81.8, 25.7, and 10.0 m, during the period between August 08, 2014 and August 07, 2015.

In the literature, there are no published short-term forecasts of the wind speed for 1, 3, 6, 9, and 12 h at four different anemometric heights in subtropical regions (south temperate zone), such as Uruguay, using and comparing the results of MLP [22], RNN, GRU, and LSTM. Therefore, this study is a novel investigation related to the operation of wind power plants for Colonia Eulacio in Soriano Department. The main contributions of the study are as follows: i) Another innovative aspect of this work is that it uses an approach to train the model for the next hour forecasting, then recursively inferring the forecasting for the following hours, in addition to applying this artificial intelligence method targeting short-range wind speed forecasting for this height using RNN, LSTM, and GRU. ii) The proposed models elucidate the behaviour of the wind speed and allows accurate wind speed prediction at different anemometric heights, e.g. 101.8, 81.8, 25.7, and 10.0 m. The model can be used to identify optimal locations of wind turbines and forecast irregular wind energy, for different anemometric heights. Short-term wind energy forecasting can be improved using this model to enhance the wind power quality 12 h ahead. iii) No previous studies applied ANN, as RNN, LSTM, GRU, and did a comparison with a classical type of neural network (MLP) for short-term wind speed forecasting for such heights in Uruguay, which is a humid subtropical climate region. Therefore, the results constitute a significant contribution to the scientific community. iv) The short-term wind speed forecasting model is an important contribution for reliable large-scale wind power forecasting and integration in Uruguay.

This work is organised as follows: Section 2 presents the methodology, Section 3 presents the numerical results and discussions, and Section 4 presents the conclusions.

2. METHODOLOGY

Regarding the computational procedure, was adopted an artificial-intelligence model using a Multilayer Perceptron, Fully-connected Recurrent Neural Network, Gated Recurrent Unit and Long Short-Term Memory ANN with Levenberg–Marquardt Backpropagation to MLP and Adam optimizer [23] to RNN, GRU, and LSTM and a training algorithm for short-term wind speed forecasting (1, 3, 6, 9, and 12 h) in Colonia Eulacio, Soriano Department, Uruguay. The mean wind diurnal cycle in different seasons for this location was described by de [10], whose analysis employed the same data used in the present study. ANN models are implemented through layers of interconnected nodes, which are called neurons, and the definition of the number of layers is variable, depending on the characteristics of the problem. At least three layers are required: an input layer, a hidden layer, and an output layer [11].

Validation employs a set of data used to calculate the error during training, for monitoring the fit level of the ANN to the training data. Generalisation is the ability of the network to respond correctly to conditions never experienced before, that is, the testing dataset. According to [12], there are different possibilities for structuring an ANN, because it is necessary to select the type of neuron, the number of input parameters, the number of hidden layers, the type of training, and the architecture configurations. To develop an ANN model, a set of input parameters and a set of output parameters are necessary. These sets are subdivided for use in two different steps: network training and validation of the produced estimates. The correct selection of the predictors is fundamental for a satisfactory performance of the model [13].

The advancement of wind energy technology has allowed for the installation of turbines at high altitudes; thus, knowledge of the wind potential at these heights is required. To validate the estimates and increase the number of wind farms installed in Soriano Department, anemometric towers with a height of 100.8 m were installed at locations with promising winds in Colonia Eulacio, which is the region considered in this study (Figure 1).

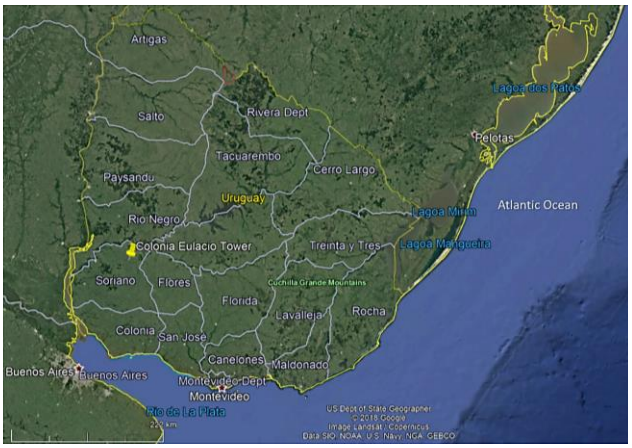

Figure 1. Location of the Colonia Eulacio Tower in Soriano Department, Uruguay [22].

As previously mentioned, the measuring station used for this study is located in the southwestern region of Uruguay (Colonia Eulacio, Soriano Department) and is composed of a triangular tower 100.8 m in height and 0.45 m wide. According to Datum WGS84, it is located at 33º 16 'S, 57º 31 'W [10]. The altitude of the installation location is approximately 100 m, and the location is surrounded by fields with plains; thus, it is characterised by non-complex terrain. The station is owned by the *Administración Nacional de Usinas y Transmissiones Eléctricas* (UTE), which is a state-owned company in Uruguay that is responsible for the generation, distribution, and commercialisation of electrical energy in the country.

The software used to program and perform this computational procedure was *MATLAB* version 7.10.0 2010, together with the NNTool (Neural Network Toolbox) graphical interface and *Pyhton* with Google Colab, Google's free cloud service for Artificial Intelligence (AI) developers, using *Keras*. The proposed ANN configurations to be analysed to MLP, RNN, GRU, and LSTM are as follows (Table 1). In this study, was applied a fully-connected network structure for RNN, GRU, and LSTM. Fully connected layers were defined using the Dense class.

Table 1. ANN configurations analysed.

ANN config.	**Layers**			
	Input node	**1st hidden layer**	**2nd hidden layer**	**Output node**
Config. 1	7	9 neur	-	1
Config. 2	7	6 neur	-	1
Config. 3	7	3 neur	-	1
Config. 4	7	1 neur	-	1
Config. 5	7	9 neur	6 neur	1
Config. 6	7	6 neur	3 neur	1
Config. 7	7	1 neur	1 neur	1

Each training and forecast simulation took, on average, 3 seconds to MLP, 8 minutes to RNN, 16 minutes to GRU, and 18 minutes to LSTM (personal computer, 8 GB RAM). The inputs for each ANN were the hour, day, month, year, and average hourly values of the wind speed, wind direction, and temperature. Therefore, the insertion of these meteorological parameters as input data contributes to efficient training of the ANN. In this sense, a descriptive statistic regarding the wind speed at different heights is shown in Table 2.

Table 2. Descriptive statistics for the wind speed.

Height [m]	**Hourly average speed [m/s]**	**Standard deviation [m/s]**
101.8	7.21	3.00
81.8	6.81	2.74
25.7	4.98	2.21
10.0	4.01	2.08

The output vector is the predicted wind speed for the next hour. The measuring height for the wind speed and wind direction is divided into four cases: 101.8 and 60.8 m; 81.8 and 60.8 m; 25.7 and 60.8 m; and 10.0 and 60.8 m. The total amount of data is 8.760 × 7 = 61.320 (100%), and the amount of data used for training and validation is 6.133 × 7 = 42.931 (70.01%). Once the best model for reproducing the real data is obtained, it is important to verify its accuracy by utilising data outside the training sample. Thus, the last 2.627 h are not considered during the training of the ANN. Therefore, the amount of data used for the forecast simulation is 2.627 × 7 = 18.389 (29.99%). Each of the aforementioned ANN configurations was trained, validated, and tested to determine which was the most efficient for short-term (1, 3, 6, 9, and 12 h) wind speed forecasting.

The activation functions, which define the outputs of the neurons in terms of their activity levels, that were inserted in this simulation were the sigmoidal function, in the form of the hyperbolic tangent function (continuous, increasing, differentiable, and nonlinear), for the hidden layers on all configurations, the linear function for the output layer on MLP and Softplus activation function for the dense output layer on RNN, GRU, and LSTM (the Softplus is enticingly smooth and differentiable; experiments show that the deep neural networks with Softplus units get significantly performance improvement). To perform the prediction, the first step is to identify what ANN architecture can best perform the 1 h forecasting of the wind speed for each height. Then, this predicted wind speed value is assigned as the input for the second hour of forecasting, while the other input parameters used at the start of the forecasting are kept unchanged (e.g. wind direction and air temperature). Thus, the forecast of the wind speed for the second hour is calculated. This procedure, which is shown in Figure 2, is repeated until the n^{th} hour of forecasting is reached.

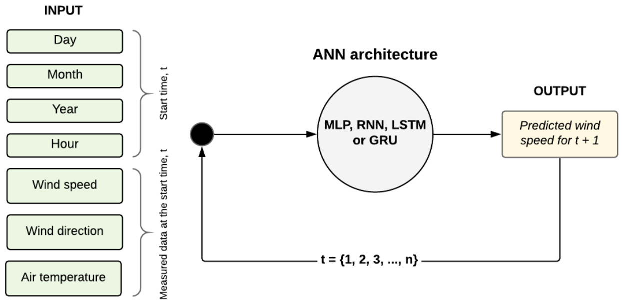

Figure 2. Schematic of the procedure used for wind speed forecasting for 1, 3, 6, 9, and 12 h after the start time.

As the prediction horizon increases, the quality of the predicted wind speed is expected to decrease, which is evaluated in the next section.

3. NUMERICAL RESULTS AND DISCUSSIONS

The statistical indicators employed to analyse the results are the Root-Mean-Square Error (RMSE), Mean Squared Error (MSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), coefficient of determination (R^2 or R-squared), and Pearson's correlation coefficient (r or Pearson's r). Values close to 0.0 are adequate for the MAE, MSE, and RMSE, values close to 0.0% are adequate for the MAPE, and values close to 1.0 are adequate for the R-squared. The Pearson's correlation coefficient ranges from −1.0 to 1.0. A value of 1.0 implies that a linear equation perfectly describes the relationship between matrices **A** and **B**, with all the data points on a line for which **B** increases as **A** increases. A value of −1.0 implies that all the data points are on a line for which **B** decreases as **A** increases. A value of 0.0 implies that there is no linear correlation between the variables.

Each ANN architecture presented in Section 2 was trained, validated, and tested using the input vector for each hour, with the wind speed of the next hour as the desired output vector. The use of a large number of hidden layers is not recommended, because the error measured during training is propagated to the previous layer. The number of neurons in the hidden layers is generally defined empirically and depends strongly on the distribution of the training and validation patterns of the network. When connected and trained in multiple layers, the ANN model can represent any nonlinear function [14]. An advantage of the ANN model is that it can learn the relationship between complex, nonlinear inputs and outputs [15]. The best ANN configurations for Colonia Eulacio are presented in Table 3. The aforementioned ANN architectures that were identified as the most efficient for the 1 h forecast for each height were applied in the computational simulation to predict the wind speed for 3, 6, 9, and 12 h in Colonia Eulacio at all the heights tested. The best MLP architecture was defined in [22].

Table 3. The best ANN configurations.

ANN / heights	101.8 m	81.8 m	25.7 m	10.0 m
	Best ANN configuration			
MLP	7	4	7	4
RNN	1	3	7	5
GRU	7	6	6	5
LSTM	6	5	1	1

The results for the MAE, MSE, RMSE, MAPE, R-squared, and Pearson coefficients for 1, 3, 6, 9, and 12 h wind speed forecasting in Colonia Eulacio are presented in Table 4 for a height of 101.8 m. The lowest values of the MAE, MSE, RMSE, and MAPE, as well as the highest Pearson's correlation coefficient and R-squared values, were recorded for the 1 h forecast for all the analysed heights (101.8, 81.8, 25.7, and 10.0 m). The mean R-squared and Pearson's r for 1 h wind speed forecasting were 0.843 and 0.918, respectively. The lowest MAPE value was 15.840%, for a height of 101.8 m and a prediction horizon of 1 h.

Table 4. Performance indices of forecasting results obtained by different models on the case study (for the height of 101.8 m).

	MLP				
Prediction Horizon [h]	1	3	6	9	12
MAE	0.89	1.67	2.24	2.59	2.87
MSE	1.40	4.68	7.95	10.3	12.38
RMSE	1.18	2.16	2.82	3.22	3.51
Coefficient: r	0.92	0.73	0.54	0.43	0.34
R^2	0.84	0.53	0.30	0.18	0.11
MAPE (%)	15.84	30.13	39.19	43.65	47.10
	RNN				
Prediction Horizon [h]	1	3	6	9	12
MAE	0.93	2.64	7.29	7.78	7.94
MSE	1.53	9.77	60.99	68.97	71.43
RMSE	1.23	3.12	7.81	8.30	8.45
Coefficient: r	0.91	0.70	0.40	0.25	0.17
R^2	0.84	0.49	0.16	0.06	0.03
MAPE (%)	17.58	63.56	173.12	183.97	187.0
	GRU				
Prediction Horizon [h]	1	3	6	9	12
MAE	0.91	1.96	6.41	8.49	8.85
MSE	1.45	5.92	47.56	80.69	87.04
RMSE	1.20	2.43	6.89	8.98	9.33
Coefficient: r	0.91	0.71	0.47	0.03	0.03
R^2	0.83	0.50	0.22	0.001	0.001
MAPE (%)	18.35	45.84	149.54	197.63	204.7
	LSTM				
Prediction Horizon [h]	1	3	6	9	12
MAE	0.89	3.45	5.85	6.08	6.13
MSE	1.43	16.15	42.22	45.03	45.71
RMSE	1.19	4.02	6.49	6.71	6.76
Coefficient: r	0.91	0.63	0.13	0.10	0.09
R^2	0.84	0.39	0.01	0.01	0.01
MAPE (%)	17.33	88.09	146.65	151.25	152.4

The results in Table 4 indicate that as the wind speed forecasting load increases, the quality of the output data of the ANN prediction decreases. Thus, a longer forecasting time yields a larger error. As explained in the previous section, these results were expected, as the adopted procedure uses input data from the start of the forecasting, in addition to the wind speed computed in each forecast hour, to predict the wind speed for the n^{th} hour, leading to an accumulated error. This result is in accordance with the literature, e.g. [16], [17], [18], and [19]. Figure 3 presents a graphical comparison of the RMSE and Pearson coefficient for different ANN model. The graph lines are of 101.8 m. The graph indicates that as the prediction horizon [h] increases, the RMSE increases, indicating that the error between the actual and predicted values increases.

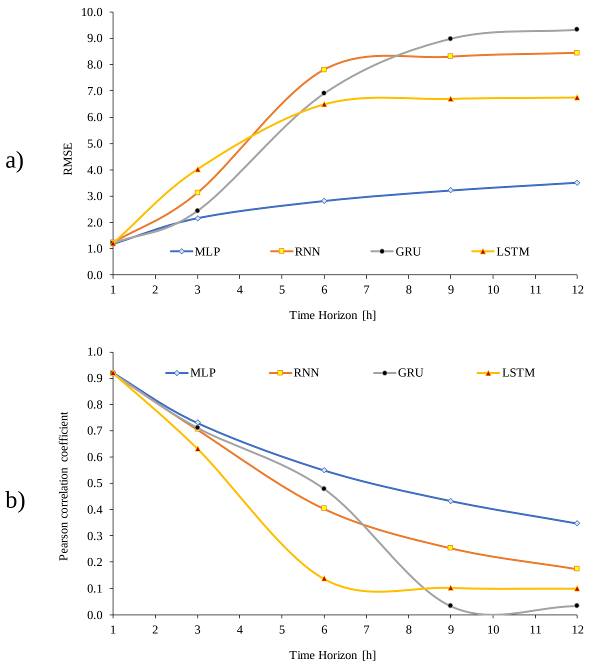

Figure 3. a) Graphical comparison of the RMSE and b) Pearson coefficient at different prediction horizon for different ANN models (height = 101.8 m).

By definition nowcasting refers to short lead time weather forecasts. The U.S. National Weather Service specifies zero to three hours, though forecasts up to six hours may be called nowcasts by some agencies. Nowcasting is usually made with techniques that differ significantly from normal numerical weather prediction models [24]. Figure 4 shows the comparison of the statistical results for the RMSE at different heights to predict the wind speed at 6 h ahead (this is important to nowcasting to short lead time wind speed forecasting) using different ANN. The best results are recorded for the MLP network, followed by LSTM neural network.

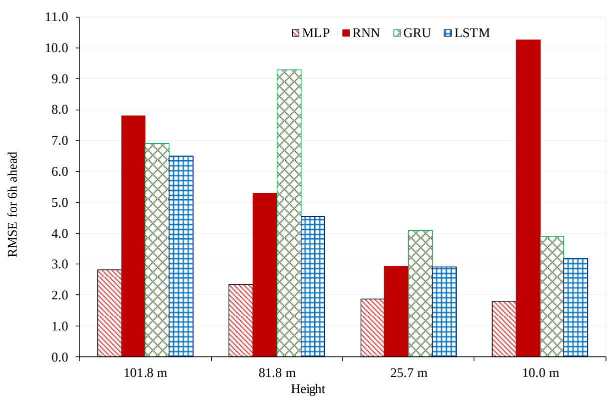

Figure 4. RMSE for 6 hours ahead using MLP, RNN, GRU, and LSTM in different heights.

Figure 5 shows the dispersion between wind speed anemometer and wind speed predicted 6 h ahead.

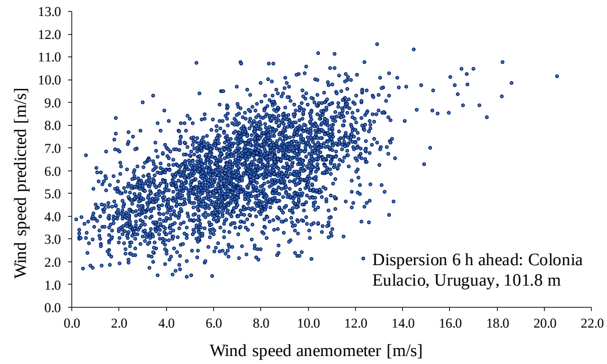

Figure 5. Dispersion's results at 101.8 m for forecast 6 h ahead.

Figure 6 presents a comparison of the results of the ANN wind speed forecasting at 6 h through MLP designed in [22], with real data, which were recorded at Colonia Eulacio with an anemometer height of 101.8 m. The ratio between the wind speed predicted by the ANN model and that measured by the anemometer can be observed with respect to time and the measured wind speed. The middle lines in the plots indicate one-to-one correspondence, and the outer lines indicate difference by a factor of two.

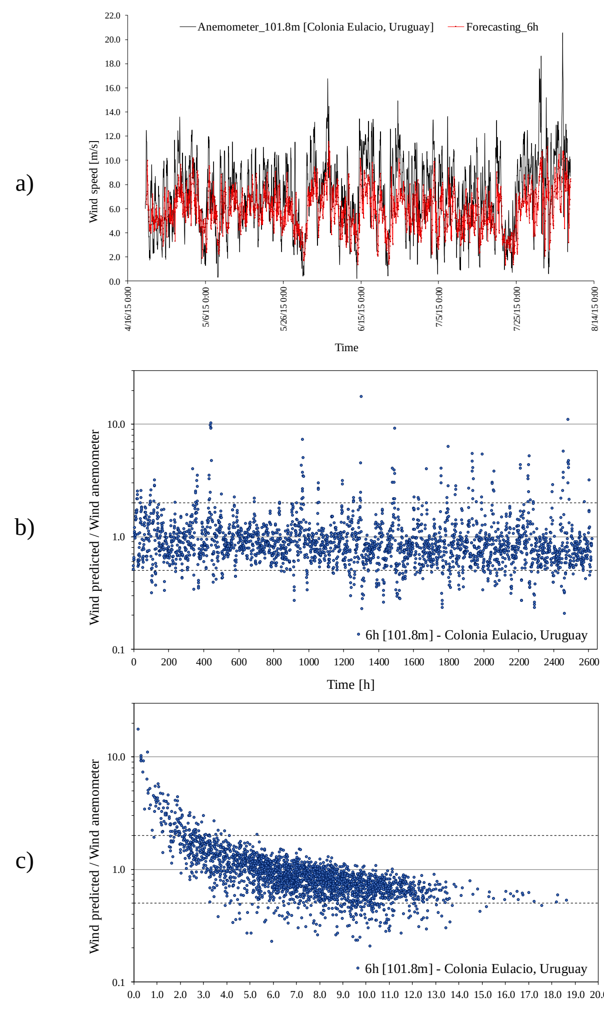

Figure 6. Wind speed forecasting at 6 h: a) The results of six-step predictions of the wind speed series. b) Comparison data of a factor of two (wind predicted/wind anemometer versus time) of

the results obtained with the forecast model (six-step predictions) and the real data. c) Comparison data of a factor of two (wind predicted/wind anemometer versus wind anemometer) of the results obtained with the forecast model (six-step predictions) and the real data.

In this study the degradation of the forecast can also be observed by noting that as the forecast horizon increases, the predicted curve moves away from the real curve. Table 5 presents the percentage of the data of a factor of two (fraction of data [%] for $0.5 \leq$ Wind predicted/Wind anemometer ≤ 2.0) to height of observed data = 101.8 m. This showed that MLP and LSTM models were the only ones that maintained results above 58% within the factor of two.

Table 5. Percentage of the data of a factor of two (height = 101.8m).

ANN model	Prediction horizon	Percentage of the data of a factor of two
MLP	1 h	98.44%
	3 h	93.29%
	6 h	88.29%
	9 h	82.43%
	12 h	77.44%
RNN	1 h	98.21%
	3 h	84.64%
	6 h	50.67%
	9 h	47.90%
	12 h	46.69%
GRU	1 h	97.79%
	3 h	93.71%
	6 h	56.92%
	9 h	43.58%
	12 h	40.69%
LSTM	1 h	98.29%
	3 h	76.94%
	6 h	60.70%
	9 h	59.05%
	12 h	58.39%

The results in Figure 7 indicate that on average, the MLP ANN has better results than the Persistence model for a prediction horizon of 1 h.

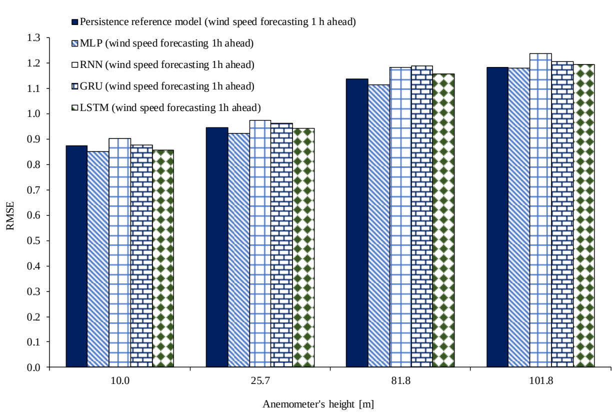

Figure 7. Comparison between the ANN models and the Persistence reference model for wind speed forecasting 1 h ahead.

The investigation of mechanisms that aid the short-term wind speed forecasting, as performed in this study for 1, 3, 6, 9, and 12 h for the generation of energy in wind farms, has been critical to ensure the proper functioning of traditional energy systems. Accurate prediction of the short-term wind speed output helps system operators to adjust scheduling plans in a timely manner, make correct decisions, reduce the standby capacity, reduce the operational costs of the power system, and mitigate the adverse effects of wind power fluctuation.

4. CONCLUSIONS

According to the statistical results of this study, the application of artificial intelligence is a viable alternative for the prediction of wind speed and thus wind power generation, mainly owing to the low computational cost. However, an ANN architecture that is appropriate for the project must be selected, and the data fed to the network must quantitatively and qualitatively be analysed, as these variables directly impact the results of the forecast. This work is relevant because it is a first step in the application of the MLP, RNN, GRU, and LSTM models to wind speed prediction, and there are no previous studies on the application of artificial intelligence using deep learning through such neural networks for this region.

The statistical results for the prediction horizons of 1 to 12 h, for each anemometric height, exhibited predictable behaviour similar to that for short time ranges. These results are novel because no other studies have used this computational model to predict the wind speed for 1, 3, 6, 9, and 12 h in Uruguay. The application of the MLP and LSTM for wind speed forecasting at different heights was adequate. From the analysis, it was found that the MLP model was superior to the other neural network's models, as they were able to achieve a relatively lower prediction error. The MLP approach here introduced uses a differentiated process of forecasting based on inference.

The surprising result is that the simplest model architecture, a multilayer perceptron (MLP), with only two hidden layers of one neuron in each of them works best among the considered architectures. This result allows one to suspect that deeper neural network architectures, ensemble or other models may be more beneficial. The 1 and 3 h forecasts were particularly accurate, and as the forecast time increased, the accuracy of the results decreased, as expected. However, this degradation did not make the forecasting results for longer prediction horizons useless; thus, the proposed technique can produce satisfactory short-term wind speed forecasts (up to 12 h) with low computational costs to help wind-farm operators with decision making.

This study contributes to the scientific community by providing wind speed forecasting information for a country of South America with high wind power potential (Uruguay), considering the interest of private companies and UTE in the energy sector. The suggestion is that futures works can be developed studying the Wavelets decomposition in the weathers data and be applied to the deep learning technology to wind speed forecasting. Wind ramp and longer forecasting horizons are also a great subject of research.

5. ACKNOWLEDGEMENTS

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