



## Short-term wind speed forecasting in Uruguay using computational intelligence

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### ABSTRACT

Short-term wind speed forecasting for Colonia Eulacio, Soriano Department, Uruguay, is performed by applying an 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 are applied for each site and height; then, a quantitative analysis is conducted, and the statistical results are evaluated to select the configuration that best predicts the real data. This method has lower computational costs than other techniques, such as numerical modelling. For integrating wind power into existing grid systems, accurate short-term wind speed forecasting is fundamental. Therefore, the proposed short-term wind speed forecasting method is an important scientific contribution for reliable large-scale wind power forecasting and integration in Uruguay. 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 Transmisiones Eléctricas manage the national energy supply.

### 1. Introduction

Renewables are sources of clean, plentiful, and potentially competitive energy sources (GE Renewable Energy, 2019). These types of energy differ from fossil fuels in their diversity and abundance and in their potential for use anywhere on the planet; above all, they produce neither greenhouse gases—which cause climate change—nor polluting emissions. Despite the present volatility of renewables, their costs are decreasing; in contrast, the costs of fossil fuels are increasing (Acciona, 2019). Currently, environmental pollution is a global issue that is receiving considerable attention, and alternative renewable resources to reduce pollution must be developed (Cheng et al., 2017). As a burgeoning type of renewable energy, wind energy has developed rapidly in the past decade (Jiang et al., 2016; Lia et al., 2018). Huang et al. (2015) 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 (Watts, 2015). In addition to old hydropower plants, large investments in solar, wind, and

biomass have increased the proportion of these sources to 55% of the total energy, significantly exceeding the global average of 12% and the European average of approximately 20%. In this sense, wind power has attracted attention, and various wind farms have been constructed in Uruguay to harness wind energy. Among the countries of the world, Uruguay ranks 4<sup>th</sup> in the generation of wind energy, according to the Renewables 2017 Global Status Report (REN21, 2017). Additionally, Uruguay has good relationships with Argentina and Brazil, which contribute to its excellent growth with regard to wind and solar energy.

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 (Liu et al., 2018). Accurate short-term wind speed forecasting (1–12 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. According to Haupt and Kosovic (2017), accurate wind speed prediction is a challenging problem that requires disparate data and multiple models that are each applicable for a specific timeframe, as well as computational-intelligence techniques

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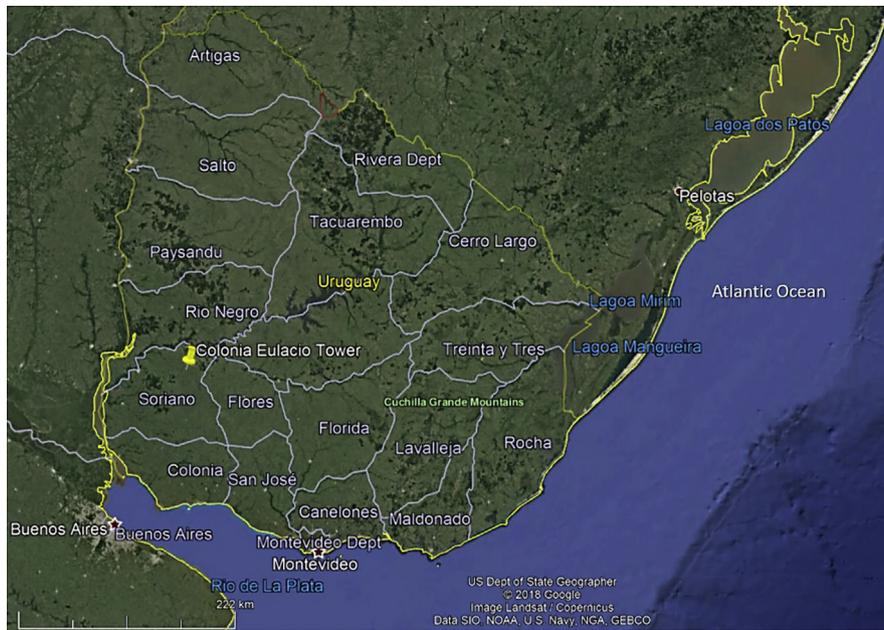


Fig. 1. Location of the Colonia Eulacio tower in Soriano department, Uruguay.

**Table 1**  
Descriptive statistics for the wind speed.

Height [m]	Hourly average speed [m/s]	Standard deviation [m/s]
101.8	7.214	3.002
81.8	6.811	2.742
25.7	4.980	2.216
10.0	4.016	2.081

for successfully blending the models and observational information in real time and delivering the results to decision makers and grid operators.

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). [Esmaeili and Twomey \(2012\)](#) explained that the large fluctuations in the wind speed make forecasting the power generated by wind turbines difficult. The spatial variation of wind energy is also very large. The topography and soil roughness significantly influence the distribution and velocity of winds. Economic losses occur if wind turbines are subjected to unfavourable weather conditions. Therefore, it is necessary to develop reliable tools to predict the wind speed, even in the short term, i.e., 1 h to several hours ahead, for economic load dispatch planning, making reasonable load decisions, and operational security in electricity markets ([Chang, 2014](#)).

Many studies have focused on the development of reliable wind speed and wind power forecasting models, and numerous models have been recently proposed (particularly in the last five years: 2014 to 2019). The mainstream models used by scientific researchers can be divided into several categories ([Jiang et al., 2016](#)): physical forecasting models (e.g. Prediktor, Previento, LocalPred, eWind, and WRF); conventional statistical forecasting models (e.g. autoregressive model, autoregressive moving average, and autoregressive integrated moving average (ARIMA)); artificial-intelligence forecasting models (e.g. feed-forward multilayer perceptron, recurrent neural network, long short-term memory, gated recurrent unit, radial basis function, Bayesian network, and extreme learning machine); statistical machine-learning models (e.g. support vector machine, least-squares support vector machine, and

Gaussian process); fuzzy logic-based models (e.g. genetic algorithm optimised fuzzy model, adaptive neuro-fuzzy inference system, Markov-switching model, and Kalman filtering); spatial-correlation forecasting models (which consider the wind speed at not only the target site but also several adjacent sites); and hybrid models. Hybrid models can be divided into two types: the first type involves the combination of individual models (e.g. ARIMA + ANN and ARIMA + extreme learning machine), and the second type employs algorithms to enhance the forecasting capacity of models (e.g. wavelet packet decomposition + ANN and genetic algorithms + ANN).

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. Interest in applications of mathematical modelling and numerical simulation of the atmosphere for the estimation of wind power potential is growing, and it already drives an important market. 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 ([Peng et al., 2013](#)). [Ren et al. \(2014\)](#), [Wasilewska and Baczynski \(2017\)](#), and [Alencar et al. \(2017\)](#), among others, obtained good results with small error via mathematical modelling and numerical simulation for short-term prediction using computational-intelligence techniques, especially multilayer perceptron neural networks with feed-forward and back-propagation training algorithms. [Alencar et al. \(2017\)](#) developed ultra-short, short, medium, and long-term prediction models for the wind speed based on artificial-intelligence and computational-intelligence techniques, including artificial neural network (ANN), ARIMA, and hybrid models, e.g. time-series forecasting using wavelets.

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 ([Zhang et al., 2017](#)). Another reason is that wind power is a non-dispatchable energy source that cannot be controlled by operators in the same way as other resources ([Erdem and Shi, 2011](#)). These challenges can be effectively resolved if the wind speed can be forecasted accurately and precisely ([Liu et al., 2010](#)). Therefore, improving the accuracy of short-term wind speed forecasting and developing improved methods are crucial for the operation of wind power plants ([Li et al., 2011](#); [Akinci, 2011](#); [Nogay et al., 2012](#); [Okumus and Dinler, 2016](#)). Recent studies on short-term wind speed forecasting,

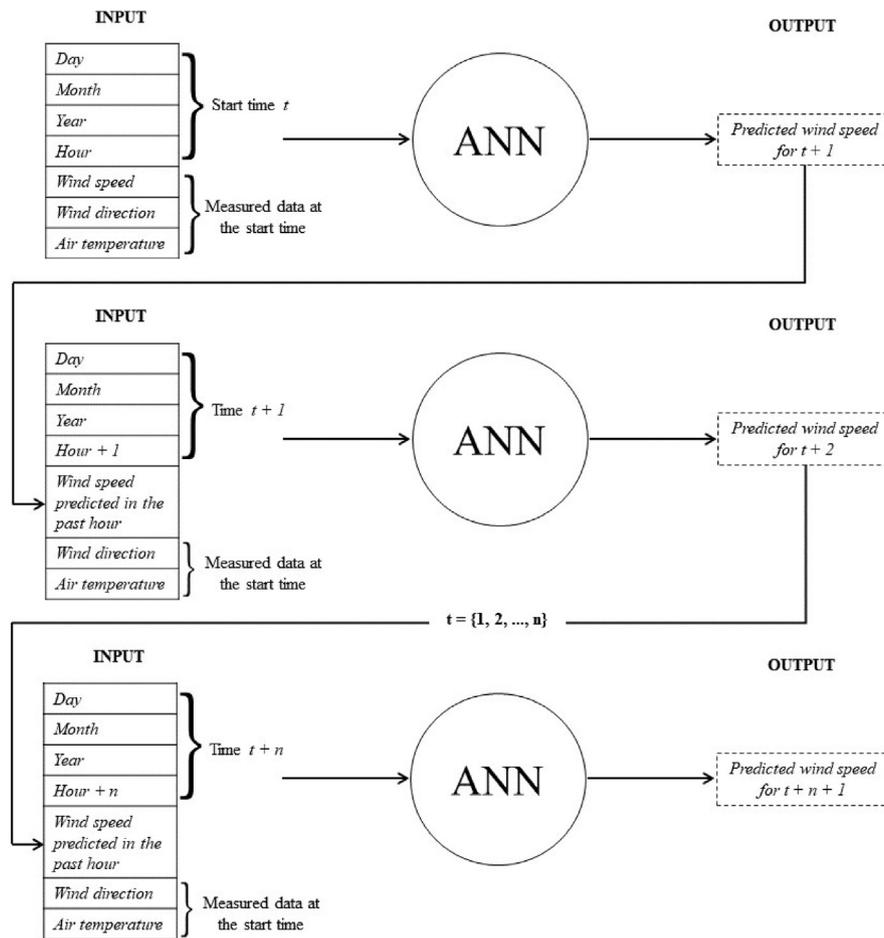


Fig. 2. Schematic of the procedure used for wind-speed forecasting for 1, 3, 6, 9, and 12 h after the start time.

**Table 2**  
Best ANN configuration for Colonia Eulacio, Soriano Department, Uruguay.

101.8 m	81.8 m	25.7 m	10.0 m
Best ANN configuration:			
7	4	7	4

e.g. those of Alencar et al. (2017), Sun et al. (2018), and Khosravi et al. (2018), revealed an increase in the forecasting error with the increase of the forecast time horizon.

López-Manrique et al. (2018) presented a work that was conducted using climatic data from Cuauhtemotzin, Mexico: wind speed, wind direction, solar radiation, air temperature, relative humidity, rain precipitation, and atmospheric pressure measured at 26, 33, and 54 m.a.g.l. From a computational methodology, a time series exogenous model was developed to forecast wind speed in 10-min intervals (very short-term wind speed forecast), using multi-gene genetic programming and global sensitivity analysis. The forecasting model considered the four previous values of the wind speed and as exogenous parameters the solar radiation, air temperature, atmospheric pressure, and relative humidity. The main difference between this work and ours relies on the fact that we are applying artificial neural networks, instead of genetic algorithms, to predict the wind speed in a time horizon of 1–12 hours ahead (short-term wind speed forecasting). Additionally, we are using meteorological data collected by anemometers from Colonia Eulacio, Soriano Department, Uruguay (a humid subtropical climate region), and not climatic data from global circulation models. It can be observed that the forecast horizon studied here is longer than what was targeted in their work, and the higher height studied here comes closer to the height of a typical wind

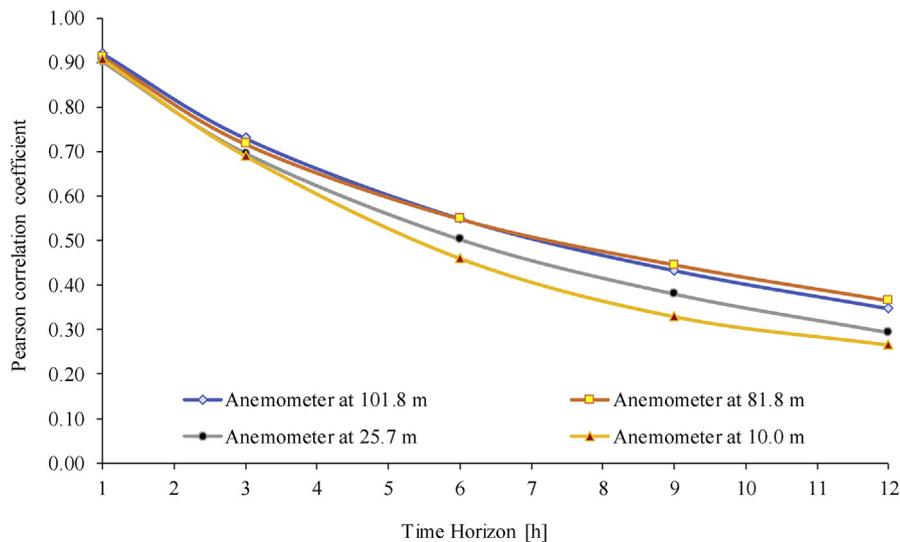
turbine (100 m) commonly used in the largest wind farms, which justifies the effort employed in this work.

Therefore, the objective of this study was to identify the most efficient ANN configuration using Multilayer Perceptrons with the Levenberg–Marquardt Backpropagation training algorithm for wind speed forecasting 1 h ahead. 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. 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. a) The proposed model elucidates 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. b) No previous studies applied computational intelligence 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. c) The short-term wind speed forecasting model is an important contribution for reliable large-scale wind power forecasting and integration in Uruguay.

This paper is organised as follows: Section 2 presents the

**Table 3**  
Simulation results: 1, 3, 6, 9, and 12-h wind-speed forecasting for Colonia Eulacio using the ANN model.

Anemometer at 101.8 m						
Prediction horizon [h]	MAE	MSE	RMSE	Coefficient: r	Coefficient: R-squared	MAPE (%)
1	0.892	1.406	1.185	0.921	0.849	15.840
3	1.678	4.683	2.164	0.730	0.534	30.137
6	2.241	7.954	2.820	0.549	0.302	39.190
9	2.595	10.380	3.221	0.432	0.186	43.658
12	2.872	12.385	3.519	0.346	0.119	47.104
Anemometer at 81.8 m						
Prediction horizon [h]	MAE	MSE	RMSE	Coefficient: r	Coefficient: R-squared	MAPE (%)
1	0.840	1.241	1.114	0.913	0.833	17.173
3	1.482	3.668	1.915	0.717	0.514	31.863
6	1.845	5.456	2.335	0.548	0.300	40.783
9	2.025	6.433	2.536	0.445	0.198	44.668
12	2.159	7.155	2.674	0.364	0.132	47.296
Anemometer at 25.7 m						
Prediction horizon [h]	MAE	MSE	RMSE	Coefficient: r	Coefficient: R-squared	MAPE (%)
1	0.690	0.854	0.924	0.902	0.813	18.954
3	1.147	2.370	1.539	0.696	0.484	32.494
6	1.409	3.500	1.870	0.502	0.252	39.206
9	1.517	4.091	2.022	0.379	0.144	41.735
12	1.574	4.461	2.112	0.292	0.085	42.800
Anemometer at 10.0 m						
Prediction horizon [h]	MAE	MSE	RMSE	Coefficient: r	Coefficient: R-squared	MAPE (%)
1	0.632	0.724	0.851	0.906	0.821	24.141
3	1.085	2.124	1.457	0.689	0.476	42.594
6	1.371	3.230	1.797	0.459	0.211	53.500
9	1.461	3.683	1.919	0.328	0.107	57.530
12	1.497	3.868	1.966	0.264	0.070	58.858



**Fig. 3.** Graphical comparison of the Pearson correlation coefficient at different heights.

methodology, Section 3 presents the numerical results and discussions, and Section 4 presents the conclusions.

## 2. Methodology

Regarding the computational procedure, we adopted a computational-intelligence model using a Multilayer Perceptron ANN with Levenberg–Marquardt Backpropagation 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 Lucas et al. (2016), whose analysis employed the same data used in the present study. According to More and Deo (2003), Wang et al. (2014), Chang (2013), and

Qin et al. (2015), this is the most commonly used type of neural network for studies of this nature. Esen and Esen (2008), Mendes and Marengo (2010), Martins et al. (2012), and Cervone et al. (2017) reported that the aforementioned algorithm is the most effective neural network training algorithm. 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 (Russel and Norvig, 2010).

All ANNs must be trained, validated, and tested. Pelletier et al. (2016) reported that network training occurs in two phases, and each phase runs through the network in one direction. These two phases are called the forward and backward phases. The forward phase is used to define the

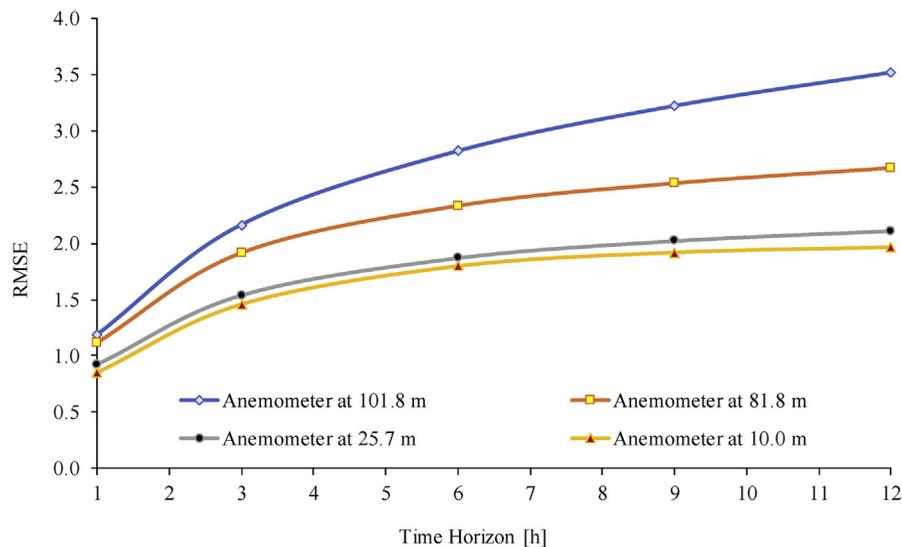


Fig. 4. Graphical comparison of the Root Mean Square Error (RMSE) at different heights.

network output for a given input pattern. The backward phase uses the desired output and the output provided by the neural network to update the weights of its connections. Knowledge is acquired by the network from its environment through a learning process, and the connecting forces between neurons, which are called synaptic weights, are used to store the acquired knowledge. The procedure used for the learning process is called a learning algorithm, and its function is to modify the synaptic weights of the network in an orderly way to achieve the project goal (Haykin, 1999).

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 Haykin (1999), 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 (Mori and Umezawa, 2009).

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 (see Fig. 1).

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 33° 16' S, 57° 31' W (Lucas et al., 2016). 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 Transmisiones 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.

As reported by Lucas et al. (2017), to verify the quality of the data observed by the anemometers of interest in the Colonia Eulacio tower,

the data were pre-processed. The data were obtained by the datalogger via measurements every 2 s, and the values were stored and a statistical average was calculated every 10 min. Additionally, the standard deviation and maximum and minimum values of the measured variables were presented. The values of interest were the average wind speeds recorded every 10 min. The configuration of the assembly and the tower on which the measuring instruments are installed significantly affect the quality and reliability of the data. After ensuring that the measurements were not affected by the tower mat, the presence or absence of missing data was verified and, after verification of the magnitudes, possible anemometer reading problems, such as “locking,” were identified. Finally, the data for one year observed at intervals of 10 in 10 min were converted to hourly values, being realised the means of the original measures measured in the interval of 60 min (1 h).

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. The proposed ANN configurations to be analysed are as follows.

Configuration 1: Three layers, seven input nodes, nine hidden neurons, and one output node.

Configuration 2: Three layers, seven input nodes, six hidden neurons, and one output node.

Configuration 3: Three layers, seven input nodes, three hidden neurons, and one output node.

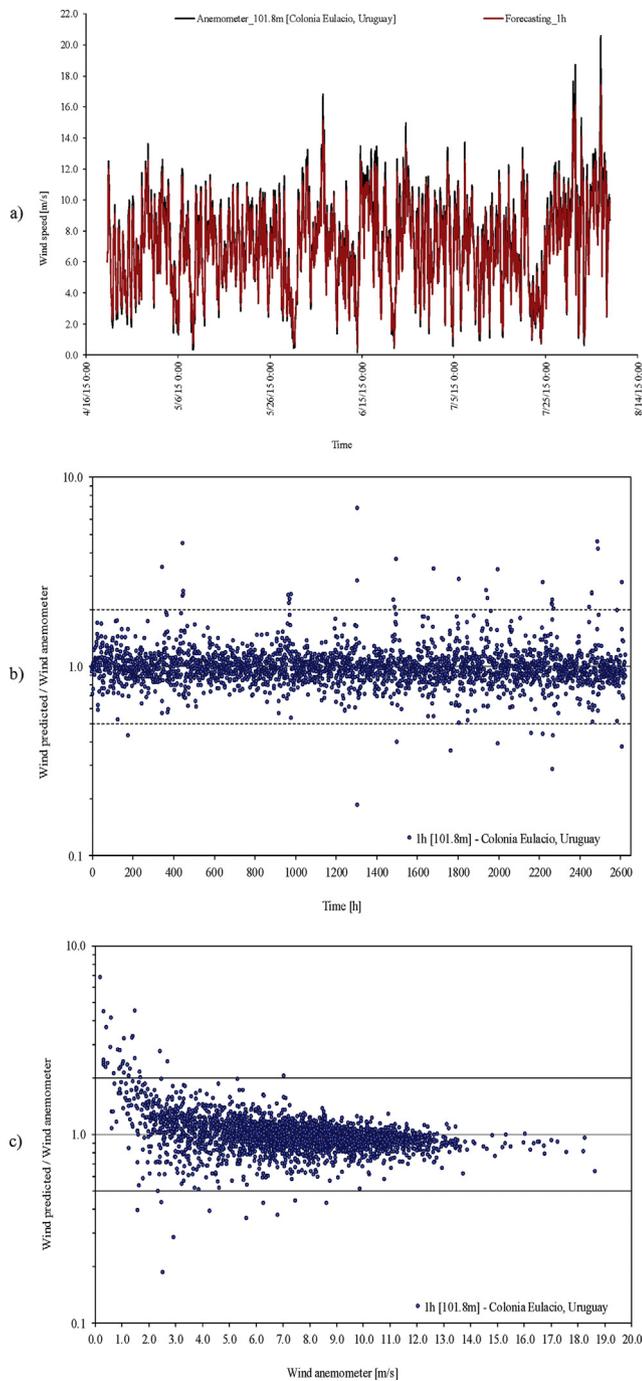
Configuration 4: Three layers, seven input nodes, one hidden neuron, and one output node.

Configuration 5: Four layers, seven input nodes, nine hidden neurons (1<sup>st</sup> hidden layer), six hidden neurons (2<sup>nd</sup> hidden layer), and one output node.

Configuration 6: Four layers, seven input nodes, six hidden neurons (1<sup>st</sup> hidden layer), three hidden neurons (2<sup>nd</sup> hidden layer), and one output node.

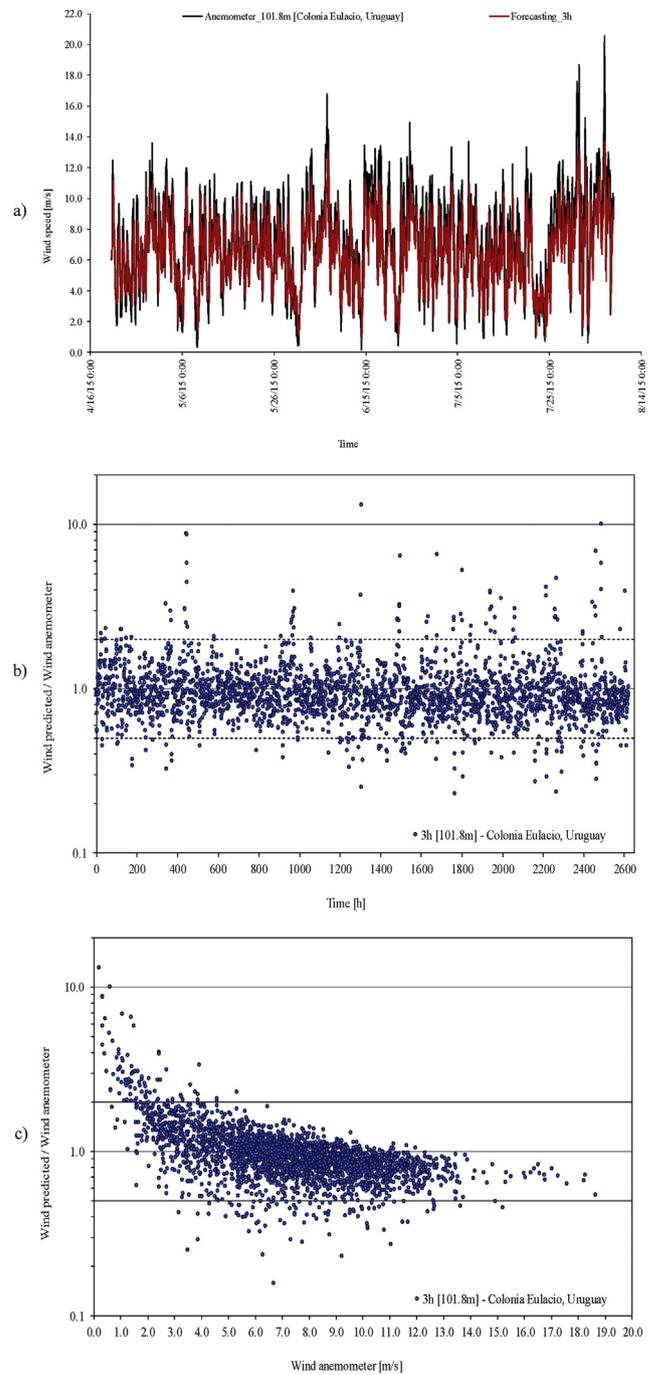
Configuration 7: Four layers, seven input nodes, one hidden neuron (1<sup>st</sup> hidden layer), one hidden neuron (2<sup>nd</sup> hidden layer), and one output node.

Each training and forecast simulation took, on average, 3 s (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. Wind is the result of the displacement of air masses. It is caused by the effects of atmospheric pressure (or barometric pressure) differences between two regions (Alencar et al., 2017) and is



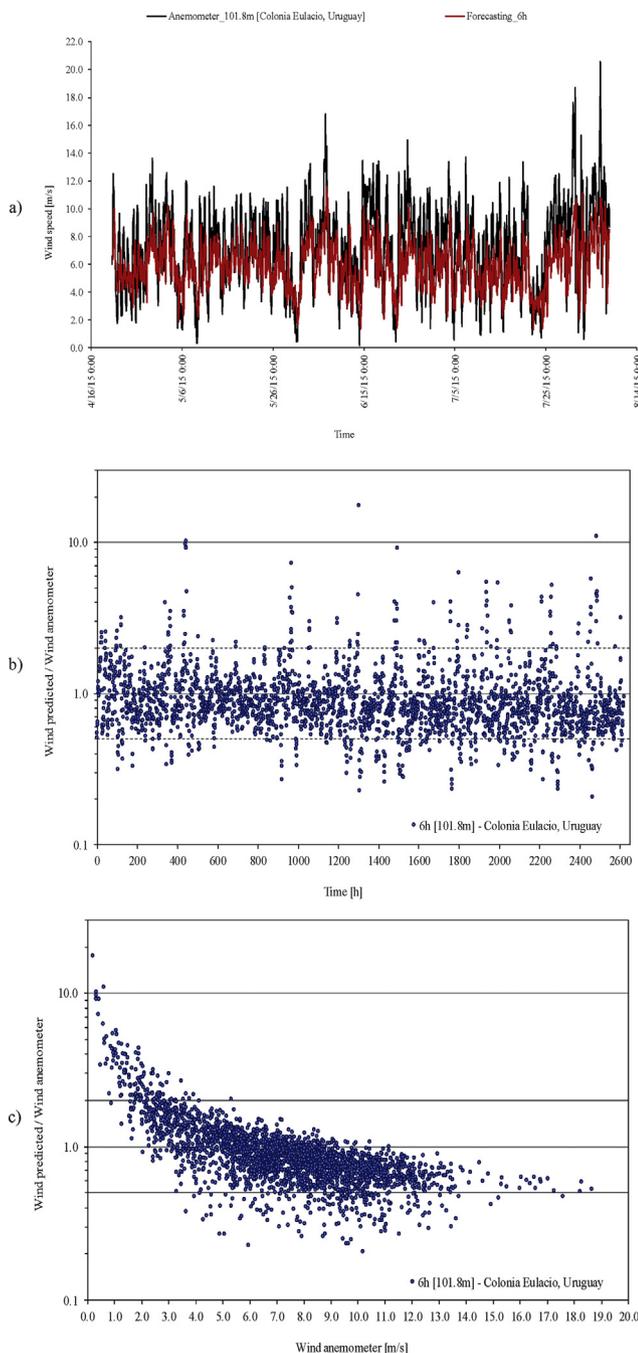
**Fig. 5.** Wind speed forecasting at 1 h: a) The results of one-step predictions of the wind speed series. b) Comparison data of a factor of two (wind predicted/wind anemometer *versus* time) of the results obtained with the forecast model (one-step predictions) and the real data. c) Comparison data of a factor of two (wind predicted/wind anemometer *versus* wind anemometer) of the results obtained with the forecast model (one-step predictions) and the real data.

influenced by natural effects such as solar radiation, continentality (a measure of the difference between continental and marine climates characterised by the increased range of temperatures that occurs over land compared with water), sea level, latitude, altitude, soil roughness, and humidity (Arya, 2001; Santos et al., 2018). 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 1.



**Fig. 6.** Wind speed forecasting at 3 h: a) The results of three-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 (three-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 (three-step predictions) and the real data.

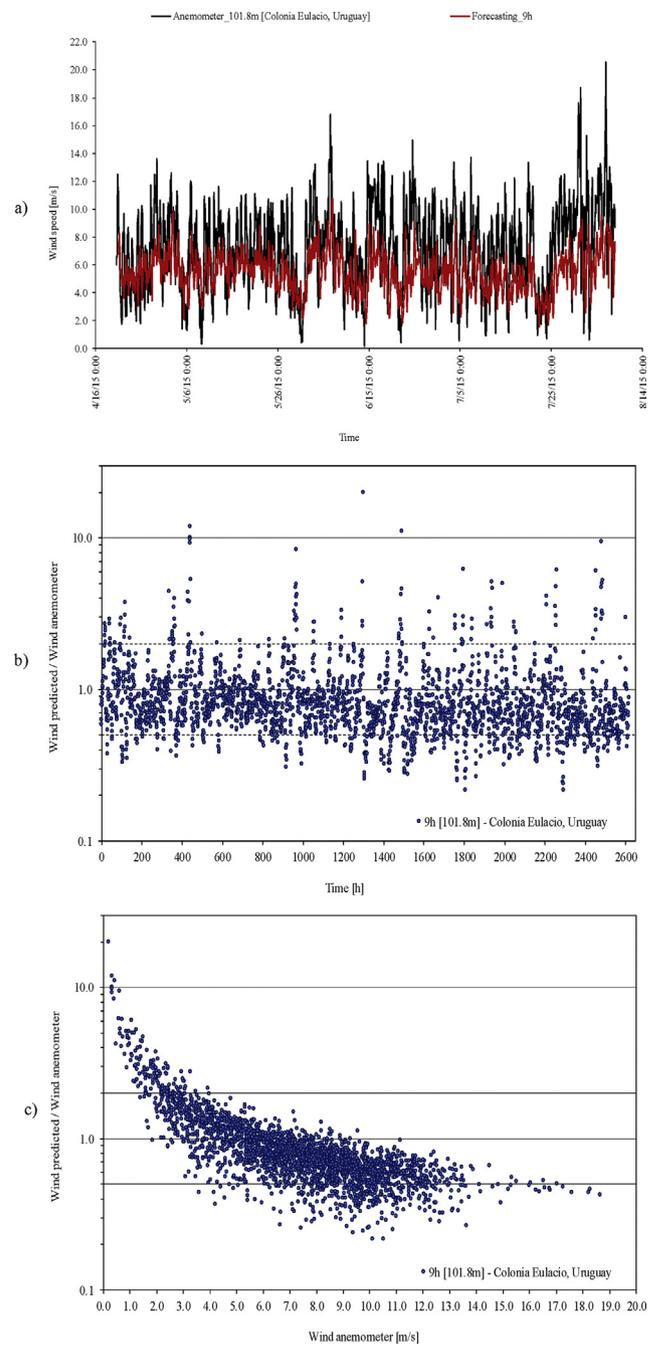
The output vector is the predicted wind speed for the next hour. The measuring height for the wind speed and wind direction is divided into four cases: 101.8 and 60.8 m; 81.8 and 60.8 m; 25.7 and 60.8 m; and 10.0 and 60.8 m. The total amount of data is  $8.760 \times 7 = 61.320$  (100%), and the amount of data used for training and validation is  $6.133 \times 7 = 42.931$  (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



**Fig. 7.** 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.

the ANN. Therefore, the amount of data used for the forecast simulation is  $2.627 \times 7 = 18.389$  (29.99%).

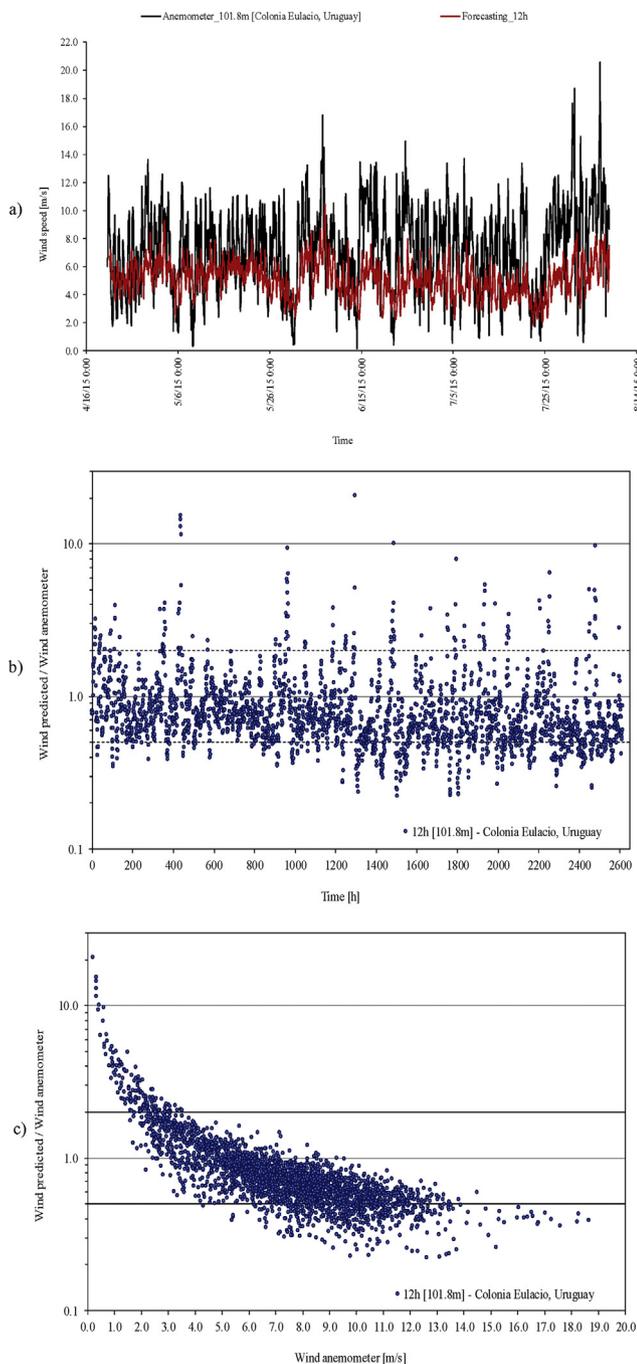
Each of the aforementioned ANN configurations was trained, validated, and tested to determine which was the most efficient for short-term (1, 3, 6, 9, and 12 h) wind speed forecasting. The activation functions, which define the outputs of the neurons in terms of their activity levels, that were inserted in this simulation were the sigmoidal function, in the form of the hyperbolic tangent function (continuous, increasing, differentiable, and nonlinear), for the hidden layers, and the linear



**Fig. 8.** Wind speed forecasting at 9 h: a) The results of nine-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 (nine-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 (nine-step predictions) and the real data.

function for the output layer. The presence of nonlinearity in the activation function of the hidden layer is important because without nonlinearity the input–output relation of the network can be reduced to that of a single-layer perceptron, as the use of the linear function in the output layer stems from the need to obtain a linear output.

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



**Fig. 9.** Wind speed forecasting at 12 h: a) The results of twelve-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 (twelve-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 (twelve-step predictions) and the real data.

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 Fig. 2, is repeated until the  $n^{\text{th}}$  hour of forecasting is reached.

Results obtained using the Persistence model were used for reference. Giebel et al. (2011) explained that the Persistence (also called the Naïve Predictor) is the model most frequently used to evaluate the performance of a forecasting model. It is one of the simplest prediction models, second only to predicting the mean value for all times, which is known as

**Table 4**

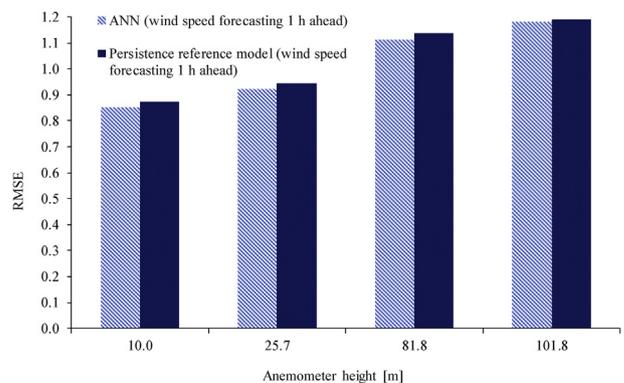
Percentage of the data of a factor of two (fraction of data [%] for  $0.5 \leq \text{Wind predicted/Wind anemometer} \leq 2.0$ ).

Height of observed data	Prediction horizon	Percentage of the data of a factor of two
101.8 m	1 h	98.44%
	3 h	93.29%
	6 h	88.29%
	9 h	82.43%
	12 h	77.44%
81.8 m	1 h	98.02%
	3 h	93.94%
	6 h	91.22%
	9 h	89.95%
	12 h	89.48%
25.7 m	1 h	97.94%
	3 h	94.25%
	6 h	91.57%
	9 h	89.95%
	12 h	88.99%
10.0 m	1 h	95.51%
	3 h	89.41%
	6 h	84.74%
	9 h	81.93%
	12 h	81.64%

climatology prediction. In the Persistence model, the forecast for all times ahead is set to the current value. Mathematically, this is expressed as  $v(t+\Delta t) = v(t)$ , where  $v$  is the wind speed [m/s] and  $t$  is time [s]. Hence, the error ( $e$ ) for  $t = 0$  (zero) time steps ahead is  $e = 0$  (zero). For short-time prediction horizons (e.g. a few minutes or 1 h), this model is the benchmark for all other prediction models (Giebel et al., 2011). As the prediction horizon increases, the quality of the predicted wind speed is expected to decrease, which is evaluated in the next section.

### 3. Results & discussion

The statistical indicators employed to analyse the results are the root-mean-square error (RMSE), mean squared error (MSE), mean absolute error (MAE), mean squared 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.



**Fig. 10.** Comparison between the ANN model and the Persistence reference model for wind speed forecasting 1 h ahead.

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. McGovern et al. (2017) explained that when connected and trained in multiple layers, the ANN model can represent any nonlinear function. Quan et al. (2013) affirmed that an advantage of the ANN model is that it can learn the relationship between complex, nonlinear inputs and outputs.

The best ANN configurations for Colonia Eulacio are presented in Table 2. 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 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 3. 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 0.829 and 0.910, respectively. The lowest MAPE value was 15.840%, for a height of 101.8 m and a prediction horizon of 1 h.

The results in Table 3 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  $n^{\text{th}}$  hour, leading to an accumulated error. This result is in accordance with the literature, e.g. Kusiak et al. (2009), Blonbou (2011), Carpinone et al. (2015), and Filik and Filik (2017).

Fig. 3 presents a graphical comparison of the Pearson coefficient for different heights and Fig. 4 presents a graphical comparison of the RMSE for different heights. The graph lines of 101.8 and 81.8 m are approximate (Fig. 3). The graph indicates that as the anemometric height increases, the RMSE increases, indicating that the error between the actual and predicted values increases (see Fig. 4).

Figs. 5, 6, 7, 8, 9 presents a comparison of the results of the ANN wind speed forecasting at 1, 3, 6, 9, and 12 h 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.

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 4 presents the percentage of data between 0.5 and 2.0. In this table, the worst values are observed for the height of 10.0 m. This result is explained by the inherently increased turbulence near the Earth's surface and its influence on the wind speed. It is assumed that as the height increases, the influence of the surface on the wind speed decreases.

The results in Fig. 10 indicate that on average, the ANN has better results than the Persistence model for a prediction horizon of 1 h.

The computational-intelligence model implemented in this study is applicable at different locations. 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.

The computational cost of using computational intelligence in studies such as the present one increases as the expected workload increases, but the cost is still lower than that of numerical simulation and mathematical modelling for wind speed forecasting using atmospheric models such as Weather Research and Forecasting (WRF) (Lucas et al., 2017). This is because in the WRF model, equations of transport phenomena and fluid mechanics are implemented and solved, such as the Euler equations for compressible and nonhydrostatic fluid in the form of fluxes using conservative variables (Skamarock et al., 2008), which demand a longer computation time. Additionally, the outputs include several meteorological parameters besides the wind speed, such as the wind direction, solar radiation, air pressure, and air temperature for every vertical layer. In comparison, neural networks and other computational-intelligence techniques require considerably less computational power, although they are limited by the need to be trained and validated against observational data for each location and height, which is not always feasible.

#### 4. Conclusions

The objective of the present study was to identify the most efficient ANN configuration for predicting the wind speed 1 h ahead and then use this model to predict the wind speed 3, 6, 9, and 12 h ahead. Observational data collected from an anemometric tower, with anemometers installed at heights of 101.8, 81.8, 25.7, and 10.0 m, were used as a reference. The study was performed for a subtropical region in Colonia Eulacio, Soriano Department, Uruguay for a period of 1 year (8760 h).

According to the statistical results of this study, the application of computational 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 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 ANN model to wind speed prediction, and there are no published studies on the application of computational intelligence through neural networks for this region. Additionally, Uruguay is a country with subtropical characteristics (temperate zone) and excellent wind technology development, and it is highly ranked internationally with regard to wind energy. The statistical results for the prediction horizons of 1–12 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 ANN for wind speed prediction at different heights was adequate. 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.

There are two main approaches for atmospheric modelling and prediction of wind fields, as applied to the energy sector: 1) the estimation of average wind speeds, taking into account climatological data, and 2) short- and medium-term wind forecasts. The first approach involves selecting sites that exhibit good wind conditions for wind power generation to provide the necessary data for evaluating the economic feasibility and to establish the parameters to be adopted in the development of generating units and wind farms. The short-term estimates are particularly useful for identifying periods of high wind occurrence, as well as the

occurrence of winds that can damage the system. Medium-term wind forecasting is useful for the management of electrical energy resources and aims to resolve deficiencies in wind power generation by providing electricity from other sources.

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.

## Declarations

### Author contribution statement

Pedro J. Zucattelli: Conceived and designed the experiments; Performed the experiments.

Erick G.S. Nascimento: Conceived and designed the experiments; Wrote the paper.

Georgynio Y.R. Aylas: Performed the experiments.

Noéle B.P. Souza: Analyzed and interpreted the data.

Yasmin K.L. Kitagawa, Alex A.B. Santos: Contributed reagents, materials, analysis tools or data.

Alejandro G. Arce, Davidson M. Moreira: Conceived and designed the experiments; Analyzed and interpreted the data.

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### Competing interest statement

The authors declare no conflict of interest.

### Additional information

No additional information is available for this paper.

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