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Study of the Wind Speed Forecasting Applying Computational Intelligence

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Abstract

The conventional sources of energy such as oil, natural gas, coal, or nuclear are finite and generate environmental pollution. Alternatively, renewable energy source like wind is clean and abundantly available in nature. Wind power has a huge potential of becoming a major source of renewable energy for this modern world. It is a clean, emission-free power generation technology. Wind energy has been experiencing very rapid growth in Brazil and in Uruguay; therefore, it's a promising industry in these countries. Thus, this rapid expansion can bring several regional benefits and contribute to sustainable development, especially in places with low economic development. Therefore, the scope of this chapter is to estimate short-term wind speed forecasting applying computational intelligence, by recurrent neural networks (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.

Keywords: atmospheric science, computer science, energy, wind engineering

1. Introduction

Since the Industrial Revolution in the eighteenth century, fossil fuels have been used as an energy source, contributing to increase the concentration of CO₂ (carbon dioxide) in the atmosphere [1]. An increasing global concentration of CO₂ in the atmosphere, from 290.0 parts per million (ppm) in 1870 [2] to 414.0 ppm in 2019 [3], occurred during the period which was marked by the Second and Third Industrial Revolution. This period is characterized by a significant increase in the use of fossil fuels as an energy source. The increased concentration of CO₂ in the atmosphere results in temperature rise. The increase in the temperature is the major cause for all other changes on the earth's climate. The rise in temperatures is causing warming of oceans, melting of ice mass, and increase in evaporation. Due to this

increase in CO₂ emissions and its consequences, the traditional concept of global development incorporated the environmental development. This incorporation resulted a broader concept referred to as sustainable development, which is based on the inseparability of economic, social, and environmental development [1]. Therefore, nowadays, integrated renewable energy system-based power generation has enormous growth and enhanced technological development due to increasing worldwide electricity demand, environmental concerns, and financial aspects [4].

In this context, renewable energy is at the center of the transition to a less carbon-intensive and more sustainable energy system. Renewable energy has grown rapidly in recent years, accompanied by sharp cost reductions for solar photovoltaics and wind power in particular [5]. Wind energy, a sustainable and a domestic source of energy that can reduce our dependency on fossil fuels, has developed rapidly in recent years. It's mature technology and comparatively low cost make it promising as an important energy source in the next decades [6]. The electricity sector remains the brightest spot for renewables energy with the exponential growth of wind power in recent years in the world [7]. **Figure 1** shows the global cumulative installed wind capacity 2001–2017 (adapted from [8]).

Brazil is a large country with regard to its sizable power system and continental distances, both in terms of grid extension and generating capacity. A prominent feature of its power system is the significance of its hydropower [9], which accounts for 59.90% [10] of the generation in the interconnected system. By the end of 2018, there were a total of 583 plants/wind farms and 14.71 GW of installed capacity, a 15.19% growth compared to December 2017, when the installed capacity was 12.77 GW. With an additional 1.94 GW, wind power now makes up 9.0% of the nation's power matrix, which also shows the percent contribution from all sources of energy to the electric power grid at the end of 2018. It is important to remember that at the end of 2017, wind power accounted for 8.10% of the energy generated [10].

Uruguay surprisingly obtains 94.0% of its electricity from renewable sources [11]. In addition to old hydropower plants, large investments in solar, wind, and biomass have increased the proportion of these sources to 55.0% of the total energy (see that the global average is 12.0% and the European average is approximately 20.0%). In this way, wind power has attracted attention, and various wind farms

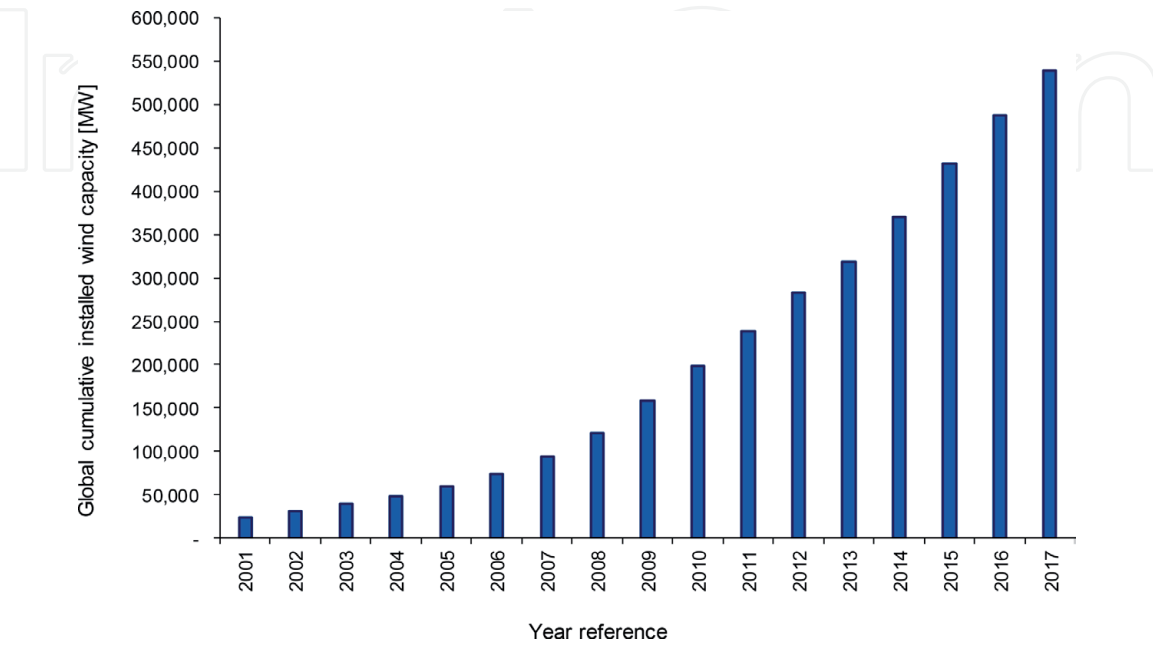


Figure 1.
Wind power global capacity 2001–2017 (adapted from [8]).

have been constructed in Uruguay to harness wind energy. Among the countries of the world, Uruguay ranks fourth in the generation of wind energy, in accordance with [12]. Additionally, Uruguay and Brazil have good relationships, which contribute to its excellent growth with regard to wind and solar energy [13].

Regarding wind power, the variability of wind speed and wind direction throughout the day makes it difficult to decide whether to drive wind turbines, because wind exhibits temporal variations of several orders of magnitude, e.g., short-duration variations (bursts), hourly variations (owing to land and sea breezes), daily variations (owing to the local microclimate), seasonal variations, and annual variations (owing to climatic changes) [13]. The spatial variation of wind energy is also very large. The soil roughness and topography significantly influence the distribution and velocity of winds. Large fluctuations in wind speed make forecasting the power generated by wind turbines difficult; not to mention that economic losses occur if these turbines are subjected to unfavorable weather conditions [14].

Consequently, it is necessary to develop reliable tools to wind speed forecasting, even in the short-range. The interest in applications of mathematical modeling and numerical simulation of the atmosphere for the estimation of wind potential is increasing and driving a significant market. The use of computational models can help both the identification of locations with high wind potential and, when used operationally in daily integrations, in the short-term energy generation forecast [15]. The mainstream models used by scientific researchers can be divided into several categories [13, 16]: physical forecasting models, conventional statistical forecasting models, artificial intelligence forecasting models, statistical machine learning models, fuzzy logic-based models, spatial-correlation forecasting models, and hybrid models.

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 [13, 15]. In [13, 17, 18], among others, they obtained good results with small error via mathematical modeling and numerical simulation for short-term prediction using computational intelligence techniques, especially multilayer perceptron neural networks with feed-forward and back-propagation training algorithms. Although the previously cited authors demonstrated the applicability of artificial neural networks (ANN) in the next-step prediction of wind speed, none of them compared the performance of the results of wind speed forecasting 6 h ahead between Colonia Eulacio, Soriano Department, Uruguay (humid subtropical climate region), and Mucuri city, Bahia, Brazil (humid tropical climate region), using meteorological data collected by anemometers and not climatic data from global circulation models shown in [19].

This chapter presents two case studies about short-term wind speed forecasting in Brazil and Uruguay. The chapter is organized as follows. In part 2, the air and the wind power are briefly described. Part 3 describes the materials and methods, computational intelligence, and nowcasting. In part 4, the case studies are proposed. Conclusions are proposed in part 5.

2. The air and wind power

The air in motion—what we commonly call wind—is invisible, yet we see evidence of it nearly everywhere we look. It transports heat, moisture, dust, insects, bacteria, and pollen from one area to another [20]. Inserted in this context, [21] explain that the winds are generated by pressure differences that arise because of unequal heating of the earth's surface. The earth's winds blow in an unending attempt to balance these

surface temperature differences. As the zone of maximum solar heating migrates with the seasons—moving northward during the Northern Hemisphere summer and southward as winter approaches—the wind patterns that make up the general circulation also migrate latitudinally. Airflow (or wind) can be divided into three broad categories: waves, turbulence, and mean wind. Each can exist in the boundary layer, where transport of quantities such as moisture, heat, momentum, and pollutants is dominated in the vertical by turbulence and horizontal by the mean wind [22]. Each can exist in the presence of any of the others or separately.

The earth’s highly integrated wind system can be thought of as a series of deep rivers of air that encircle the planet. Embedded in the main currents are vortices of various sizes, including hurricanes, tornadoes, and midlatitude cyclones. Like eddies in a stream, these rotating wind systems develop and die out with somewhat predictable regularity. In general, the smallest eddies, such as dust devils, last only a few minutes, whereas larger and more complex systems, such as midlatitude cyclones and hurricanes, may survive for several days [21]. The scales of atmospheric motion shown in **Table 1** illustrate the three major categories of atmospheric circulation: microscale, mesoscale, and macroscale (synoptic scale and global scale).

In short, wind is the movement of air from an area of high pressure to an area of low pressure. In fact, wind exists because the sun unevenly heats the surface of the earth. As hot air rises, cooler air moves in to fill the void. As long as the sun shines, the wind will blow. And wind has long served as a power source to humans [23]. Wind spins the blades, which turn a shaft connected to a generator that produces electricity, in other words, wind turbines convert kinetic energy contained in the wind first into mechanical and then into electrical energy [24]. Wind is a clean source of renewable energy that produces no air or water pollution. And since the wind is free, operational costs are nearly zero once a turbine is erected. Mass production and technology advances are making turbines cheaper, and many governments offer tax incentives to spur wind-energy development [23].

Nowadays, wind turbine technology is considered matured, and the costs of wind energy are low [6]. Industry experts predict that if this pace of growth continues, by 2050 one third of the world’s electricity needs will be fulfilled by wind power [23]. Though wind power has performed well in recent years, it also creates a strong environmental impact, such as visual impact, climatic impact, and noise. Although these impacts seem minor when compared with nonrenewable energy, its effect on humans should not be overlooked, due to its potential great development in usage. In short, with proper and supportive policies toward wind power and a good understanding of its environmental impact, wind energy can be a clean and sustainable source of energy that can successfully replace fossil fuels [6].

Scale	Typical size	Phenomenon	Life span
Microscale	0–1.0 km	Small turbulent eddies, thunderstorms	Seconds to minutes
Mesoscale	1.0–100 km	Tornadoes, waterspouts, dust devils, land/sea breeze, mountain/valley breeze	Minutes to hours/days
Synoptic scale	100–5000 km	Hurricanes, tropical storms	Days to weeks
Global scale	1000–40,000 km	Longwaves in the westerlies, trade wind	Weeks to years

Table 1.
Scales of atmospheric motion (adapted from [20, 21]).

3. Materials and methods

In this chapter, we use computational intelligence by artificial neural networks for the next-step prediction of one climatic variable: wind speed. ANN was trained to perform the forecasting of 1 h ahead, and then, using it, the trained network was applied to recursively infer the forecasting for the next 6 h of the wind speed (now-casting), following the methodology explained in [13]. The activation functions that define the outputs of the neurons in terms of their activity levels, inserted in this simulation, were the sigmoidal function in the form of the hyperbolic tangent function (characterized as continuous, increasing, differentiable, and nonlinear) for hidden layers and linear function to the output layer.

To train the RNN and validate the technique, anemometer data (average hourly values of wind speed, wind direction, and temperature) for 1 year (August 08, 2014, and August 07, 2015) are collected by one tower with anemometer installed at height of 101.8 m to Colonia Eulacio (Uruguay), and data (average hourly values of wind speed, wind direction, temperature, humidity, and pressure) for 1 month (November 30, 2015, until December 31, 2015) are collected by one tower with anemometers installed at height of 100.0 m to Mucuri (Brazil), using the same criteria as in [13], namely, 70% for training/validating data and 30% for simulation. The reason for choosing these periods is these are the months with the totality of data available for the realization of this study.

The Mucuri city (Bahia, Brazil) is located at an altitude of 7.0 m in relation to the sea level, and it has a territorial area of 1775 km², approximately. Mucuri's anemometer tower is located in a coastal plain, at a distance of 340.0 m from the sea, with latitude 18°1'31.52" S and longitude 39°30'51.69" W (**Figure 2**).

As for Colonia Eulacio Tower in Uruguay, according to datum WGS84, it is located at 33°16' S, 57°31' W [25]. The altitude of the installation location (see **Figure 3**) is approximately 100.0 m, and the location is surrounded by fields with plains; thus, it is characterized by noncomplex 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 commercialization of electrical energy in the country, as cited in [13].

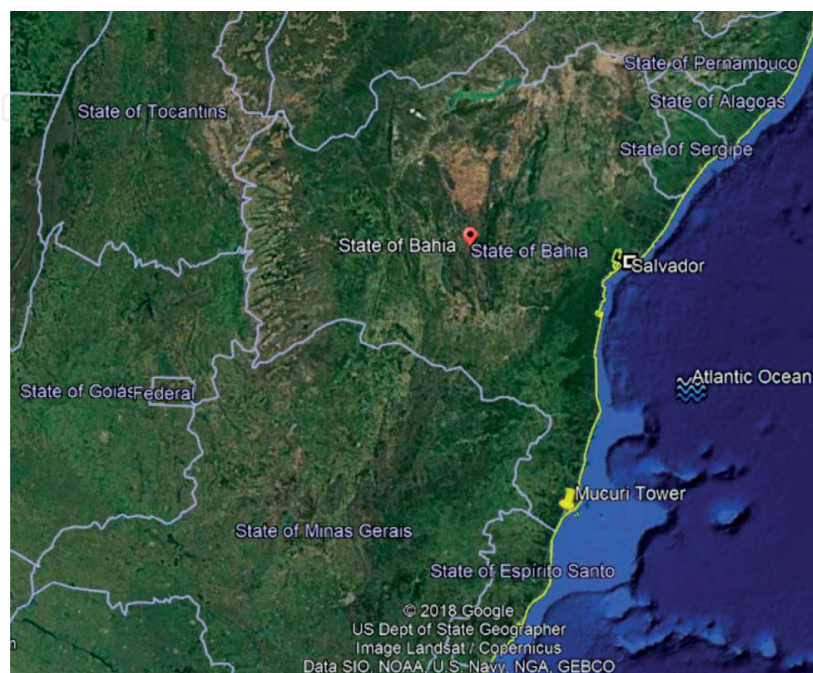


Figure 2.
Location of the Mucuri Tower in Bahia, Brazil.

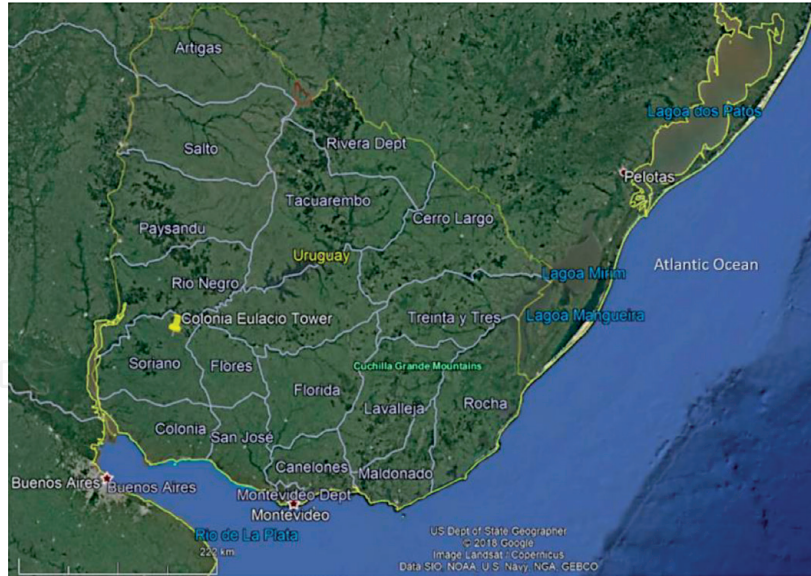


Figure 3.
Location of the Colonia Eulacio Tower in Soriano Department, Uruguay [21].

The insertion of meteorological parameters as input data contributes to efficient training of the ANN. Seven different ANN configurations are applied for each site and height; then, a quantitative analysis is conducted, and the statistical results (MAE, MSE, and RMSE) are evaluated to select the configuration that best predicts the real data. The proposed ANN configurations to be analyzed are the following ones. For Mucuri (Brazil) the best ANN configuration was Configuration 1 and for Colonia Eulacio (Uruguay) was the Configuration 4.

1. Configuration 1: three layers, nine input nodes (site, Brazil) or seven input nodes (site, Uruguay), nine hidden neurons, and one output node
2. Configuration 2: three layers, nine input nodes (site, Brazil) or seven input nodes (site, Uruguay), six hidden neurons, and one output node
3. Configuration 3: three layers, nine input nodes (site, Brazil) or seven input nodes (site, Uruguay), three hidden neurons, and one output node
4. Configuration 4: three layers, nine input nodes (site, Brazil) or seven input nodes (site, Uruguay), one hidden neuron, and one output node
5. Configuration 5: four layers, nine input nodes (site, Brazil) or seven input nodes (site, Uruguay), nine hidden neurons (first hidden layer) and six hidden neurons (second hidden layer), and one output node
6. Configuration 6: four layers, nine input nodes (site, Brazil) or seven input nodes (site, Uruguay), six hidden neurons (first hidden layer) and three hidden neurons (second hidden layer), and one output node
7. Configuration 7: four layers, nine input nodes (site, Brazil) or seven input nodes (site, Uruguay), one hidden neuron (first hidden layer) and one hidden neuron (second hidden layer), and one output node

For statistical analysis of wind speed prediction results at the above sites, the following statistical indicators were applied: Pearson's correlation coefficient

(r or Pearson's r), coefficient of determination (R^2 or R-squared), mean absolute percentage error (MAPE), mean absolute error (MAE), mean squared error (MSE), and root mean square error (RMSE). Pearson's correlation coefficient ranges from -1.0 to 1.0 . 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 software used to program and perform this computational procedure was MATLAB version 7.10.0 (2010) (personal computer, 8 GB RAM), as the methodology applied in [13].

3.1 Computational intelligence and nowcasting

Computational intelligence (CI) is the theory, design, application, and development of biologically and linguistically motivated computational paradigms. Over the last few years, there has been an explosion of research on machine learning and deep learning. Nowadays, deep learning has become the core method for artificial intelligence (AI) [26]. AI is one of the newest fields in science and engineering. AI currently encompasses a huge variety of subfields, ranging from the general (learning and perception) to the specific, such as playing chess, proving mathematical theorems, writing poetry, driving a car on a crowded street, diagnosing diseases, and predicting the conditions of the atmosphere for a given location and time. AI is relevant to any intellectual task; it is truly a universal field [27]. In fact, some of the most successful AI systems are based on CI.

In the early days of artificial intelligence, the field rapidly tackled and solved problems that are intellectually difficult for human beings but relatively straightforward for computers—problems that can be described by a list of formal, mathematical rules [28]. Many artificial intelligence tasks can be solved by designing the right set of features to extract for that task, then providing these features to a simple machine learning algorithm. The most widely used artificial neuron model is the perceptron proposed in [29, 30]. This model defines a neuron composed of inputs, a summation and an activation function. The value of each input is multiplied by a weight, and the weighted values of the inputs are summed to yield the result of the sum which is used as the input of the activation function. To teach (train) the neuron, the weights are modified so that the output obtained corresponds to the desired value [30].

The multilayer perceptron (MLP) consists of a system of simple interconnected neurons, or nodes, which is a model representing a nonlinear mapping between an input vector and an output vector. The architecture of a MLP is variable but in general will consist of several layers of neurons. The input layer plays no computational role but merely serves to pass the input vector to the network. The terms input and output vectors refer to the inputs and outputs of the MLP and can be represented as single vectors [31]. Moreover, in relation to recurrent neural network (RNN), the definition is that they are powerful sequence-processing models that are equipped with a memory from recurrent feedback connections. One of the current main challenges of RNN is to dynamically adapt to multiple temporal resolutions and scales in order to learn hierarchical representations in time. Since they operate in discrete time steps and update at every time step, it is generally difficult to learn temporal features that have a significantly different resolution than their input frequency [32].

Predicting the short-term power output of a wind turbine (wind energy converter) is an important task for the efficient management of smart grids. Short-term forecasting at the minute scale also is known as nowcasting. By definition nowcasting refers to short lead time weather forecasts, the US National Weather Service specifies zero to 3 h, though forecasts up to 6 h may be called nowcasts by

some agencies [33]. Nowcasting is critical when managing operations of the smart grid, such as system integration, ensuring power continuity and managing ramp rates [34]. In this chapter, nowcasting refers to short-term wind speed forecasting 6 h ahead. In [35] they described and evaluated a proposal for nowcasting wind speed for wind farm locations from historical time series, based on the method of regression by support vectors (in short, nowcasting of wind speed using support vector regression: experiments with time series from Gran Canaria).

4. Brazilian and Uruguayan case study: Mucuri municipality, tropical region, and Colonia Eulacio, subtropical region

The figures below show the time series used in the models which consist of 744 h for Mucuri in Brazil (Figure 4) and 8760 h for Colonia Eulacio in Uruguay (Figure 5), corresponding to hourly mean wind speed data. As can be observed in the figures, there is noticeable data randomness, and it is difficult to find a series tendency or seasonality.

In this sense, a descriptive statistic regarding wind speed at different sites is shown in Table 2. It can be noted that wind speed data measured at Colonia Eulacio has a higher variability.

Tables 3–6 show the evaluation metrics of the prediction results obtained by the proposed model. Table 3 presents simulation results referring to errors in wind speed forecasting 1, 3, and 6 h ahead for Mucuri using the RNN model. In Table 4, we present the results for regression for Mucuri. In Table 5, we can see errors in wind speed forecasting 1, 3, and 6 h ahead for Colonia Eulacio using the RNN model. Table 6 shows the regression results to Colonia Eulacio. The percentage of the data of a factor of two is a fraction of data [%] for $0.5 \leq \text{wind predicted/wind anemometer} \leq 2.0$. Table 4 shows that the percentage of the data of a factor of two [%] to Mucuri is bigger than the percentage of the data of a factor of two [%] to Colonia Eulacio (see Table 6).

Figures 6–8 show the results of six-step predictions of the wind speed series to Colonia Eulacio and to Mucuri. In Figure 6, we observe wind speed forecasting results of the model with RNN in six-step ahead for Colonia Eulacio, Uruguay. Figure 7 presents wind speed forecasting 6 h ahead in a period of 744 ho of

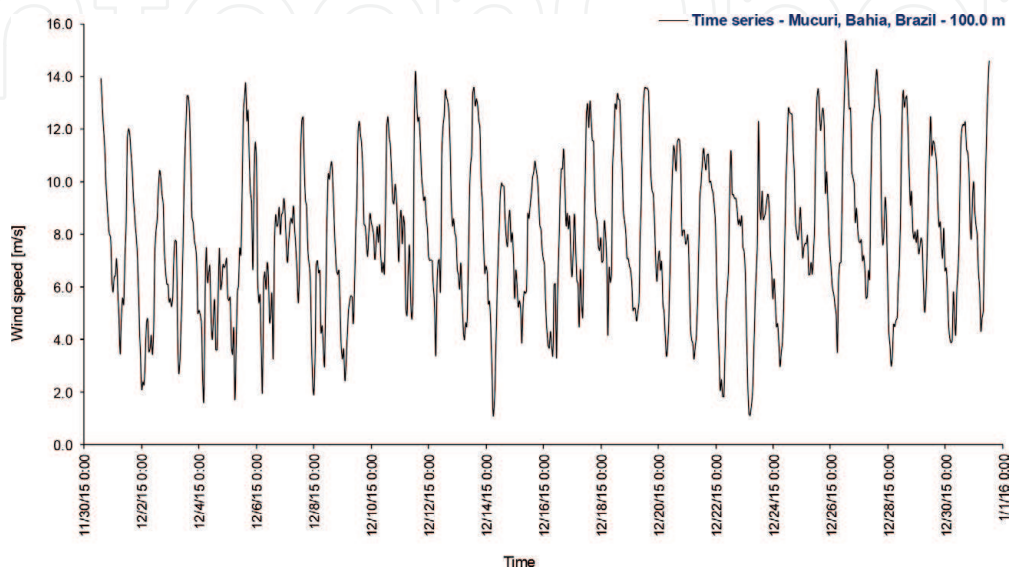


Figure 4. The experimental wind speed time series—Mucuri (Brazil).

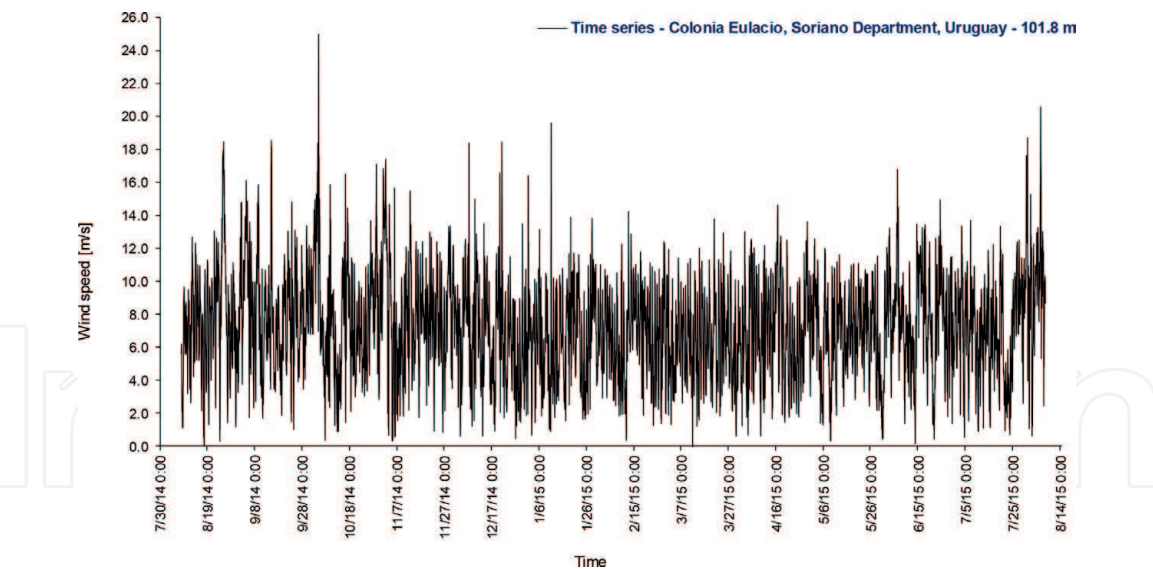


Figure 5.
The experimental wind speed time series—Colonia Eulacio (Uruguay).

Site	Arithmetic mean of wind speed [m/s]	Variance [m ² /s ²]	Standard deviation [m/s]
Mucuri	7.91	8.53	2.92
Colonia Eulacio	7.21	9.02	3.00

Table 2.
Statistics (Mucuri and Colonia Eulacio).

Prediction horizon [h]	MAE	MSE	RMSE	MAPE [%]
1	0.839	1.111	1.054	11.07
3	1.385	3.154	1.775	17.63
6	1.779	5.108	2.260	21.26

Table 3.
Simulation results (errors): wind speed forecasting 1, 3, and 6 h ahead for Mucuri using the RNN model.

Prediction horizon [h]	Pearson correlation coefficient	Coefficient R ²	Percentage of the data of a factor of two [%]
1	0.940	0.885	99.48
3	0.850	0.723	98.95
6	0.742	0.550	98.94

Table 4.
Simulation results (regression): wind speed forecasting 1, 3, and 6 h ahead for Mucuri using the RNN model.

anemometric tower measurements. In **Figure 8**, we can see wind speed forecasting results of the model with RNN in six-step ahead for Mucuri, Brazil.

Figures 9 and **10** show the multistep root mean square error (RMSE) evaluation of RNN and MLP for Mucuri, Brazil, and Colonia Eulacio, Uruguay. It is observed in **Figure 9** that as the prediction horizon increases, RNN were more efficient when compared to those employed in the study which applies MLP referenced by [36]. These results indicate that if we want a higher accuracy in the result to Mucuri, we must use a

Prediction horizon [h]	MAE	MSE	RMSE	MAPE [%]
1	0.895	1.408	1.187	16.08
3	1.687	4.710	2.170	30.65
6	2.266	8.051	2.837	39.86

Table 5.
Simulation results (errors): wind speed forecasting 1, 3, and 6 h ahead for Colonia Eulacio using the RNN model.

Prediction horizon [h]	Pearson correlation coefficient	Coefficient R ²	Percentage of the data of a factor of two [%]
1	0.922	0.849	98.44
3	0.729	0.531	93.60
6	0.543	0.295	88.52

Table 6.
Simulation results (regression): wind speed forecasting 1, 3, and 6 h ahead for Colonia Eulacio using the RNN model.

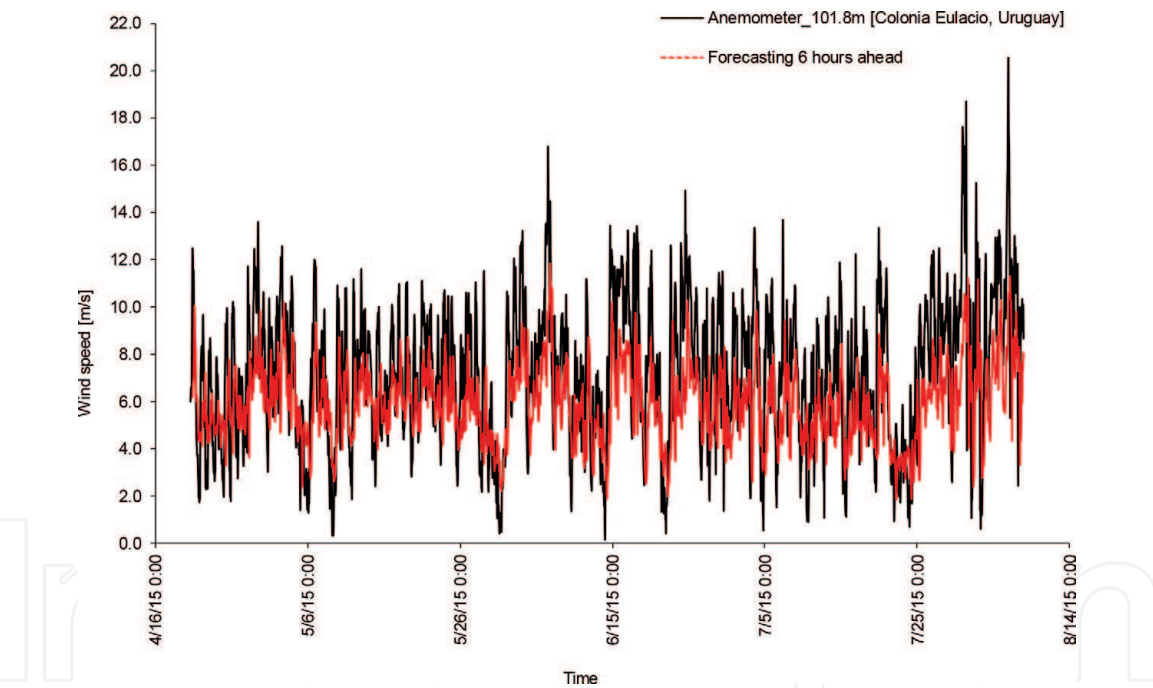


Figure 6.
Wind speed forecasting results of the model with RNN in six-step ahead (Colonia Eulacio, Uruguay).

recurrent neural network. A recurrent neural network allows self-loops and backward connections between all neurons in the network. That enables the networks to do temporal processing and learn sequences, e.g., temporal association/prediction.

Unlike the previous comparison, for Colonia Eulacio’s anemometers data, the study which applies MLP referenced by [13] was more appropriate (**Figure 10**) than this study that applies RNN.

The multistep Pearson correlation coefficient evaluation of different architecture and site is shown in **Figure 11**.

The computational cost employed to simulate wind speed prediction through RNN for Colonia Eulacio is not viable when compared to the application of MLP. In

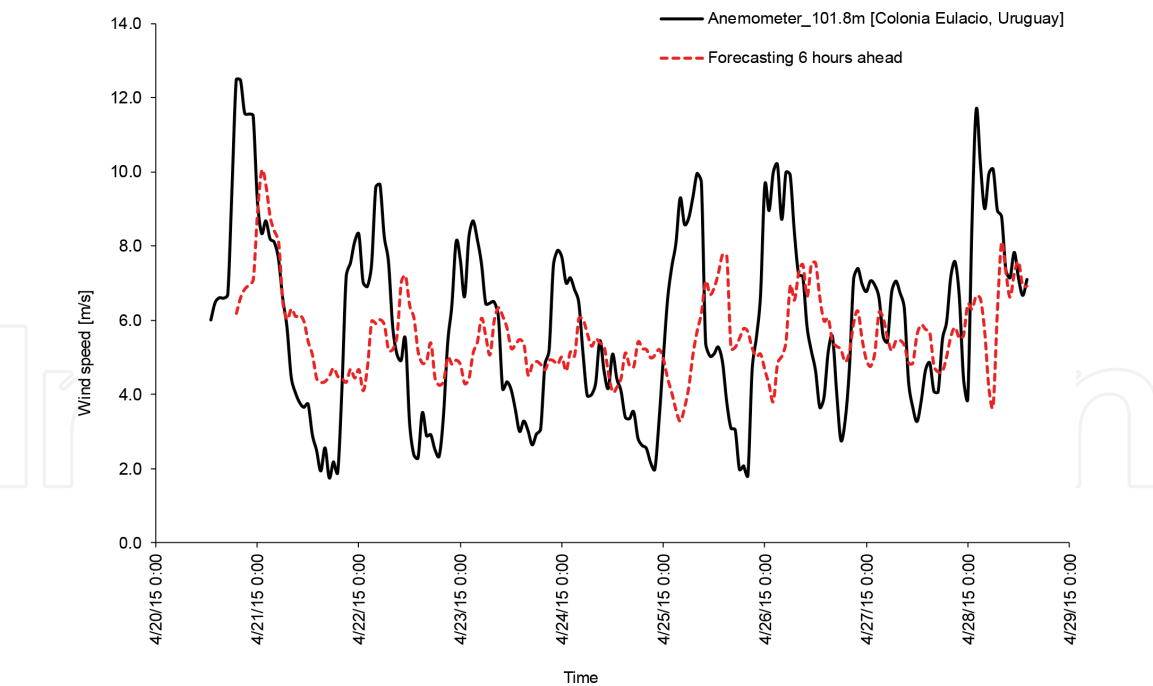


Figure 7.
Wind speed forecasting results of the model with RNN in six-step ahead (Colonia Eulacio, Uruguay), April 20, 2015, at 13:00 to April 28, 2015, at 14:00.

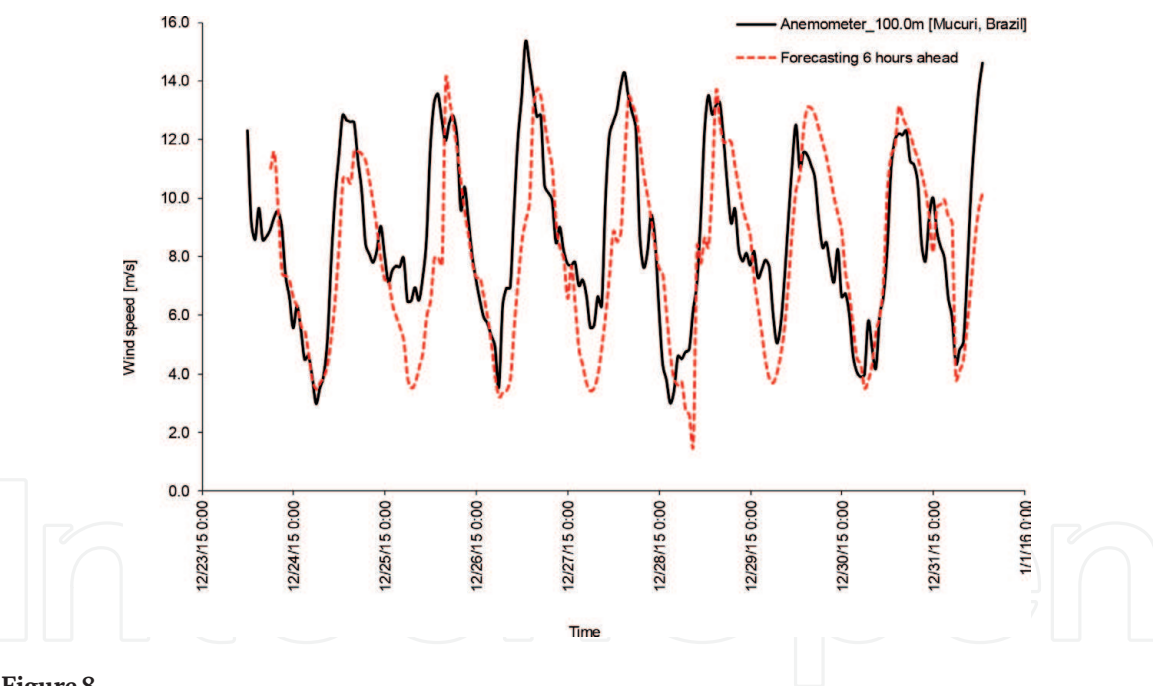


Figure 8.
Wind speed forecasting results of the model with RNN in six-step ahead (Mucuri, Brazil).

contrast, for Mucuri, it is considerably more viable to apply RNN, as can be seen from the figure above. Lastly, nowadays, adopting renewable energy has become a national energy policy for many countries due to concerns with pollution from fossil fuel consumption and climate change. Regarding wind energy, the accurate prediction of wind is crucial in managing the power load. Thus, this work presented the short-term wind speed forecasting for two representative sites in South America, Brazil, and Uruguay, which are the most important countries in terms of renewable energy production in Latin America.

Each scientific study on wind speed prediction has its own characteristics, such as the height of the anemometer that records atmospheric data (e.g., wind speed,

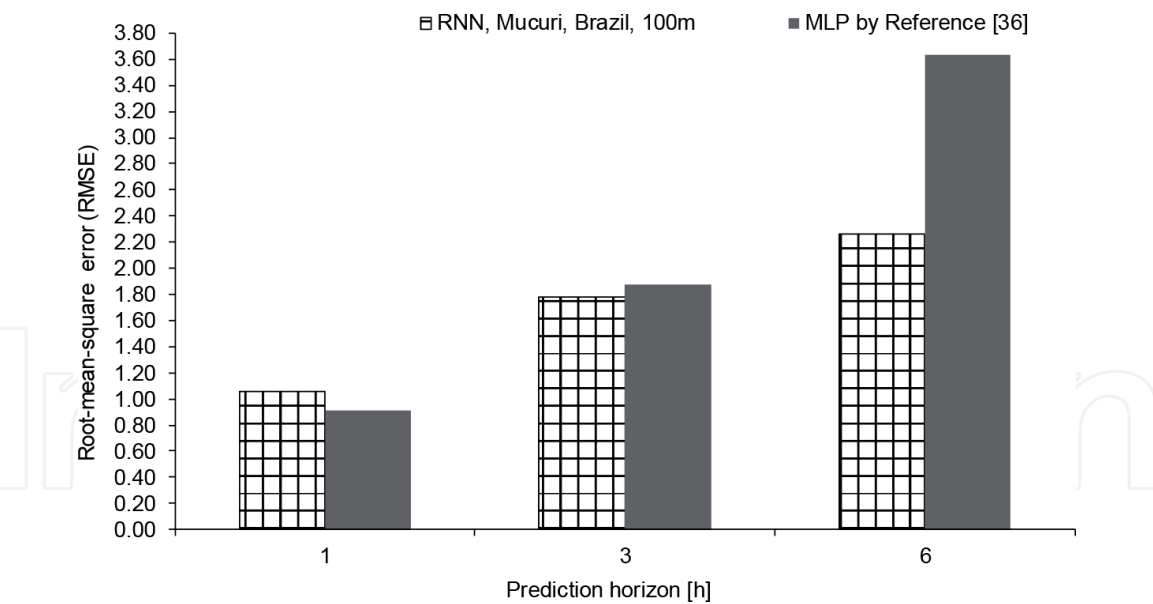


Figure 9.
The multistep root mean square error evaluation of different architecture for Mucuri, Brazil.

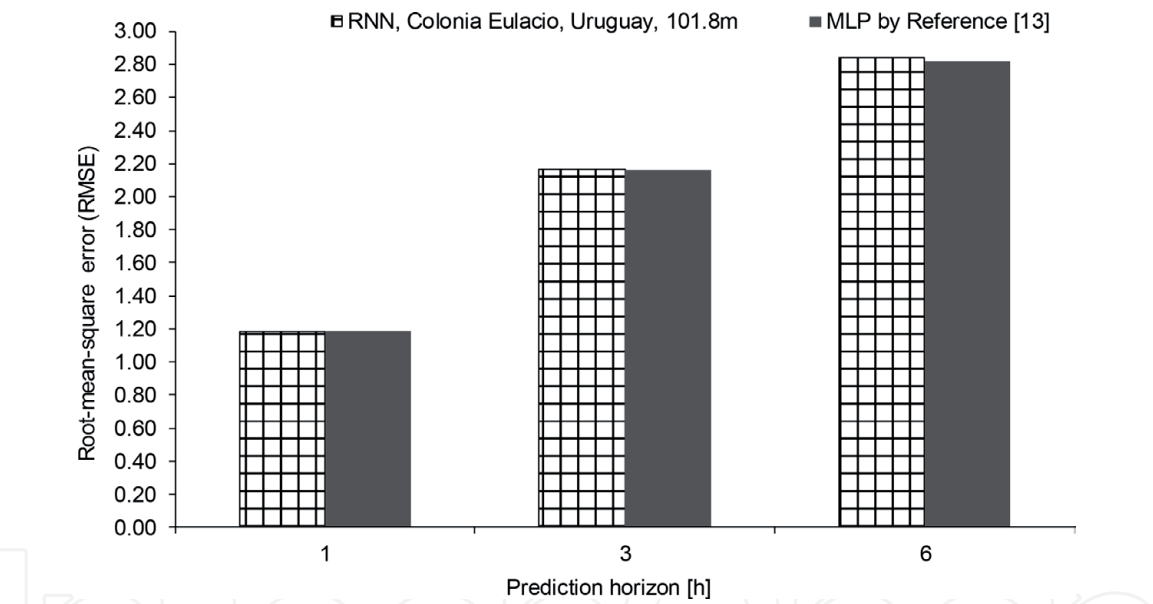


Figure 10.
The multistep root mean square error evaluation of different architecture for Colonia Eulacio, Uruguay.

direction, temperature, humidity, and atmospheric pressure) and the time series of this atmospheric data. These data are applied to train and test the efficiency of the ANN. On the accuracy of the use of ANN in the estimation of short-term wind speed and wind power forecasting, we can mention these earlier studies (see **Table 7**). The MAE average value for 1 h ahead was 0.847 m/s and for 3 h ahead was 1.420 m/s.

Other scientific research on wind speed has been developed. We can cite the works in [39, 40]. In [39] they analyzed the time series of wind speeds in Mucuri, Mucugê, and Esplanada, cities of the state of Bahia, and the Abrolhos Archipelago, Brazil, through the use of the detrended fluctuation analysis technique to verify the existence of long-range correlations and associated power laws. Already [40] describes a short-term wind energy forecasting tool based on a run set forecasting system of the WRF-GFS model that has been operationally implemented in the electricity system in Uruguay with estimates for Brazil wind energy production.

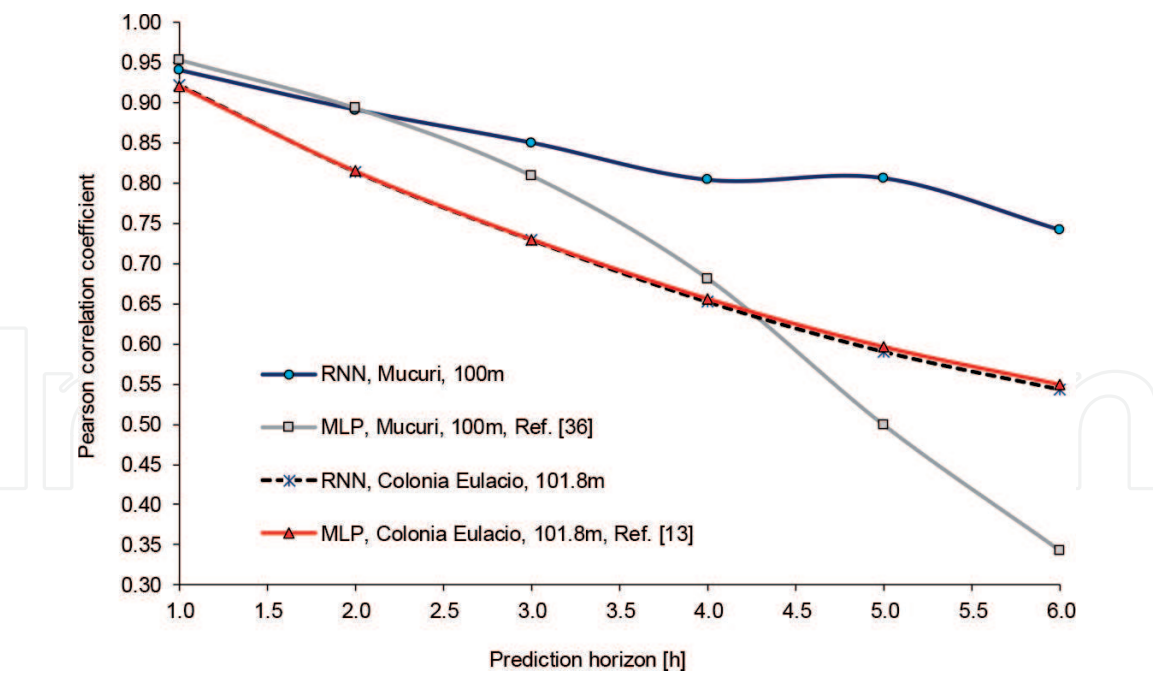


Figure 11.
The multistep Pearson correlation coefficient evaluation of different architecture and site.

Prediction horizon [h]	Mucuri: this study	Colonia Eulacio: this study	Reference [13]	Reference [36]	Reference [37]	Reference [38]
Mean absolute error						
1	0.839	0.895	0.892	0.720	1.050	0.684
3	1.385	1.687	1.678	1.370	1.230	1.168

Table 7.
Accuracy of the use of ANN in the estimation of wind speed and wind power.

5. Conclusions

The present chapter aimed to define the most efficient RNN configuration to predict the wind speed for 1 h and, after that, to apply it for 6 h ahead, using as reference observational data collected from two anemometric towers, with anemometers installed at 100.0 and 101.8 m height, located, respectively, in a tropical region in Mucuri, Bahia, northeastern Brazil, and in a subtropical region in Colonia Eulacio, Soriano Department, Uruguay. It has been shown graphically and verified through numerical simulations that the RNN was better than MLP in Mucuri and worst in Colonia Eulacio.

In the light of the statistical results recorded in this work, the application of computational intelligence is a viable alternative for the predictability of wind speed and, in this way, wind power generation, mainly due to the low computational cost; however, one must choose the ANN architecture that best suits the project, as well as quantitatively and qualitatively analyzes the available data that will feed the network, since these variables directly impact the results of the forecast.

The results of the short-term wind speed forecasting showed good accuracy at all the anemometer heights tested. Therefore, the proposed short-term wind speed forecasting method is an important scientific contribution for reliable large-scale wind power forecasting and integration in tropical and subtropical regions, like in Brazil and Uruguay.

The suggestion for improving the accuracy of ANN for higher lead time is wavelet packet decomposition because the empirical wavelet transform can effectively identify and extract a finite number of intrinsic modes of a wind speed time series and thus improving the accuracy of the supervised machine learning; other suggestion is to apply the wind speed x-axis component and wind speed y-axis component ANN's input.

We can suggest as future work to use the Mucuri, Colonia Eulacio, and other observational data collected in different heights in Brazil and Uruguay to perform the prediction of the wind speed more accurately in the short-term and in the medium-term using computational intelligence by long short-term memory (LSTM) and gated recurrent unit (GRU) and to compare these results with the output produced by numerical and meteorological modeling using the weather research and forecasting (WRF) model, for example. Wind ramp and greater forecasting horizons are also a great subject of research.

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Conflict of interest

The authors declare no conflict of interest.

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