An Interdisciplinary Machine Learning Approach for Wind Speed Forecasting[1]

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Abstract

Multidisciplinary researchers have collaborated with industry to develop advanced high-fidelity simulation and optimization tools for wind power plants and turbine interactions with the atmosphere. These tools are capable of modeling the processes needed to predict plant interactions and provide state-of-the-art simulation and analysis capabilities that allow industry stakeholders to perform a wide variety of forecasting and optimization to lower the energy costs and mechanical impacts. Insights from machine learning and computational intelligence have the potential to transform nearly every aspect of the world as we know it. Today, these insights are being applied to accelerate the pace of discovery in a wide variety of areas including materials science, wind and solar energy, health care, national security, emergency response, and transportation. In order to provide effective wind speed forecasting, an interdisciplinary approach based on artificial intelligence (AI) by supervised machine learning with human judgment is presented in this work. An approach is proposed for a representative site in the Colonia Eulacio, Soriano Department, Uruguay. The statistical results are evaluated, and a quantitative interpretation given to choose the machine learning configuration that best forecasts the actual data. These machine learning methods have lower computational costs than other techniques such as numerical models for weather or climate prediction. The proposed method is a scientific contribution to reliable large-scale wind energy prediction and integration into existing

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grid systems in Soriano, Uruguay, and is a powerful tool that can help the UTE manage the national energy supply.

Keywords: *Atmospheric Science; Interdisciplinary Communication; Machine Learning; System Sciences and Engineering; Wind Speed Forecasting.*

1. Introduction

The integrity of natural ecosystems is already at risk from climate change caused by the intense emissions of greenhouse gases (or GHG emissions) such as carbon dioxide, methane, nitrous oxide, hydrofluorocarbons, perfluorocarbons, and sulfur hexafluoride into the atmosphere. Air pollution is currently a global issue that has received considerable attention. Alternative renewable resources such as solar and wind power must be developed to reduce global greenhouse gas emissions and, consequently, air pollution (Cheng et al., 2017). Nowadays, the adaptation of renewable energy (the most common examples include solar, wind, biomass, geothermal, hydropower, hydrogen, geothermal, and ocean energy) has become a national energy policy for many countries.

Wind energy has developed rapidly in the past ten years (Jiang et al., 2016; Lia et al., 2018). This burgeoning type of renewable energy has showed exponential growth between 2010 and 2020. It was reported in Huang et al. (2015) that wind energy has the largest market share among renewable energy sources and is expected to maintain its rapid growth in the coming decade. The country of Uruguay, which is in South America, the fourth largest continent in the world, surprisingly obtains 94% of its electricity from renewable sources (Watts, 2015) mainly in the form of solar and wind power. Among the countries of the world, Uruguay ranks 3rd in the generation of wind energy (REN21, 2020). Wind speed prediction is fundamental in the monitoring, planning, and control of intelligent wind power systems. However, owing to the intermittent and stochastic nature of wind, it is difficult to make satisfactory forecasts (Liu et al., 2018).

Wind energy varies over time. The variations occur mainly due to the influence of meteorological fluctuations over various time scales of within a minute, within an hour, from hour to hour, monthly and seasonally, and across years. Understanding these variations and their predictability is of key importance for the integration and optimal utilization of wind in the power system. Accurate short-term wind speed forecasting (1 h to 12 h ahead) plays a substantial role in addressing this challenge. The correct prediction of wind speed can reduce the risk of wind power breaking in hybrid energy systems.

Computational tools have been used to evaluate the wind behavior and thus obtain valuable information for the electro-energy sector in several parts of the world. Computational models can be useful for the identification of locations with high wind potential and, when used operationally in a daily and integrated manner, provide short, medium, and long-term wind energy generation forecasts (Peng et al., 2013). The use of wind energy generation for powering industries and society in general is very challenging for current power system operations. One reason for this is the fact that wind power is an intermittent energy source with a high degree of randomness and instability (Zhang et al., 2017).

Artificial intelligence (AI), machine learning, and deep learning are among the most important soft computing methods that are widely used in a large range of applications spanning across various scientific fields. Short-term wind speed prediction for Colonia Eulacio, Soriano Department, Uruguay, has been performed by applying an artificial neural network (ANN) technique to representative hourly time series data for the site (Zucatelli et al., 2019a). The authors adopted an AI model using an multilayer perceptron (MLP) ANN with the Levenberg–Marquardt backpropagation learning algorithm. An MLP is a class of feed-forward ANN. The ANN in that work was first trained to provide the forecast for the next 1 hour ahead and using the forecast, the trained network was then applied recursively to infer the wind speed forecast for the next 12 h. The results of the short-term wind speed prediction showed good accuracy at all the anemometer heights tested, suggesting that this method is a powerful tool that can help the *Administración Nacional de Usinas y Trasmisiones Eléctricas* (UTE) manage the generation, transmission, distribution, and commercialization of electrical energy in Uruguay.

Zucatelli et al. (2019b) reported short-term wind speed forecasting for the next 6 h ahead (nowcasting) through the application of computational intelligence. The forecast was generated by an recurrent neural network (RNN) using anemometer data collected by anemometric towers at heights of 100.0 m in Brazil (tropical region) and 101.80 m in Uruguay (subtropical region). Both Brazil and Uruguay are Latin American countries. The results of the study were compared with wind speed prediction results from the literature. The prediction results from the method proposed in the study achieved superior evaluation metrics (error, and regression).

As an example of nowcasting, Zucatelli et al. (2019c) presented an application of the ANN technique to representative hourly time series data for short-term wind speed prediction at a site in the tropical region of Mucuri city, Bahia state, Brazil. To generate the training, validation, and test sets for this technique (supervised machine learning), one month of data was collected in a tower with anemometers installed at the heights of 100 m, 120 m, and 150 m. Different ANN configurations were applied with aim of finding the most efficient MLP ANN configuration with the Levenberg–Marquardt backpropagation training algorithm to forecast the wind speed for the next one hour ahead. The configuration was then applied to forecast the wind speed for the next three and six hours ahead. The coefficient of determination and the Pearson coefficient for the wind speed prediction for one hour ahead were 0.890 and 0.943, respectively. The statistical results show that the application of the ANN technique to predict the wind speed at the higher heights at the Bahia site has good accuracy and demonstrate its applicability as a powerful tool to help National Electrical System Operator (ONS) improve the usage and integration of wind energy into the national electrical grid.

Zucatelli et al. (2019d) studied the use of a supervised machine learning algorithm that applied the MLP, RNN, and wavelet decomposition techniques to representative time series data of the site to generate short-term wind speed predictions in the tropical region of Mucuri city, Bahia state, Brazil. To train the ANN and validate the technique (supervised machine learning), data for one month were collected by an anemometric tower at a height of 100 m. Different wavelet families and ANN configurations were applied for this site and height. Based on the results of the study cases, it can be concluded that the proposed method (RNN + discrete Meyer wavelet, or dmey, level 3) provided the best results for the short-term forecasting horizon.

In this context, the objective of this study is to identify the most efficient ANN configuration applying fully-connected RNN, gated recurrent unit (GRU), and long short-term memory (LSTM) with the Adam optimizer training algorithm for wind speed prediction 1 h ahead, and perform a comparison with MLP researched and developed in Zucatelli et al. (2019a). The Adam optimization algorithm is an extension to stochastic gradient descent (SGD) that has recently seen broader adoption in computer vision and natural language processing deep learning applications (Kingma et al., 2014). The algorithm has also been applied for 1 h to 12 h forecasts using anemometer data collected from a tower located in Colonia Eulacio, Soriano Department, Uruguay, which is used as a reference in this current study. Anemometers were installed at the heights of 10.0 m, 25.70 m, 81.80 m, 101.80 m between August 08, 2014, and August 07, 2015. There are no published reports in the literature for short-term 1 h to 12 h forecasts of the wind speed at four different anemometric heights in subtropical regions (south temperate zone), which include Uruguay, using and comparing the results of MLP (Zucatelli et al., 2019a), RNN, GRU, and LSTM. Thus, this study is a novel investigation relevant to the operation of wind energy plants in Uruguay. The main contributions of the study are as follows:

i) One innovative aspect of this work is that it uses an approach to train the model for next-hour forecasting and then recursively infers the forecast for the following hours by applying artificial intelligence methods targeting short-term wind speed forecasting for the specified heights using RNN, LSTM, and GRU.

ii) The proposed computational models based on AI by supervised machine learning elucidate the wind speed behavior and allow accurate wind speed prediction at different anemometric heights, e.g. 10.0 m, 25.70 m, 81.80 m, and 101.80 m. The model can be used to identify optimal locations for wind turbines and to predict irregular wind energy for different anemometric heights at different sites. Short-term wind energy prediction can be improved using this model to enhance the wind power quality 1 h to 12 h ahead.

iii) No previous research had applied the RNN, LSTM, and GRU ANNs and performed a comparison against a classical neural network (e.g. MLP) for short-term wind speed prediction at the studied heights in Uruguay, which is a humid subtropical climate region. Thus, the results constitute a significant contribution to the scientific community.

iv) The short-term wind speed prediction model is an important contribution to reliable large-scale wind energy forecasting and integration in Uruguay, given the increased use of this energy source in this country.

The remainder of this paper is organized as follows: the methodology is presented in section 2. Section 3 presents the numerical results and discussions, and the conclusion is given in section 4.

2. Methodology

Artificial intelligence models (ANN models) by supervised machine learning using MLP with Levenberg–Marquardt Backpropagation, and fully-connected RNN, GRU, and LSTM with the Adam optimizer (Kingma et al., 2014) were adopted as the computational methods. A training algorithm was applied for short-term wind speed prediction 1 h to 12 h ahead at Colonia Eulacio, Soriano Department, Uruguay at the anemometer's heights of 10.0 m, 25.70 m, 81.80 m, and 101.80 m. The mean wind diurnal cycle in different seasons for this location was described in Lucas et al. (2016), which employed the same data for analysis as that used in the present study. ANN models are implemented through layers of interconnected nodes called neurons. The number of layers may vary depending on the characteristics of the problem. At least three layers are required: an input layer, a hidden layer, and an output layer (Russel & Norvig, 2010). A concise definition of the AI field, by Chollet (2018), would be as follows: "the effort to automate intellectual tasks normally performed by humans". Chollet (2018) explain that "a machine-learning system is trained rather than explicitly programmed. It's presented with many examples relevant to a task, and it finds statistical structure in these examples that eventually allows the system to come up with rules for automating the task". He defines that "deep learning is a specific subfield of machine learning: a new take on learning representations from data that puts an emphasis on learning successive layers of increasingly meaningful representations". For Chollet (2018), "the deep in deep learning isn't a reference to any kind of deeper understanding achieved by the approach; rather, it stands for this idea of successive layers of representations". Other definitions found in the literature, no less important, are highlighted in Figure 1. It shows an illustration of the relationship between computational or artificial intelligence, machine learning, and deep learning. Machine learning algorithms can be classified into different types as shown in Figure 2.

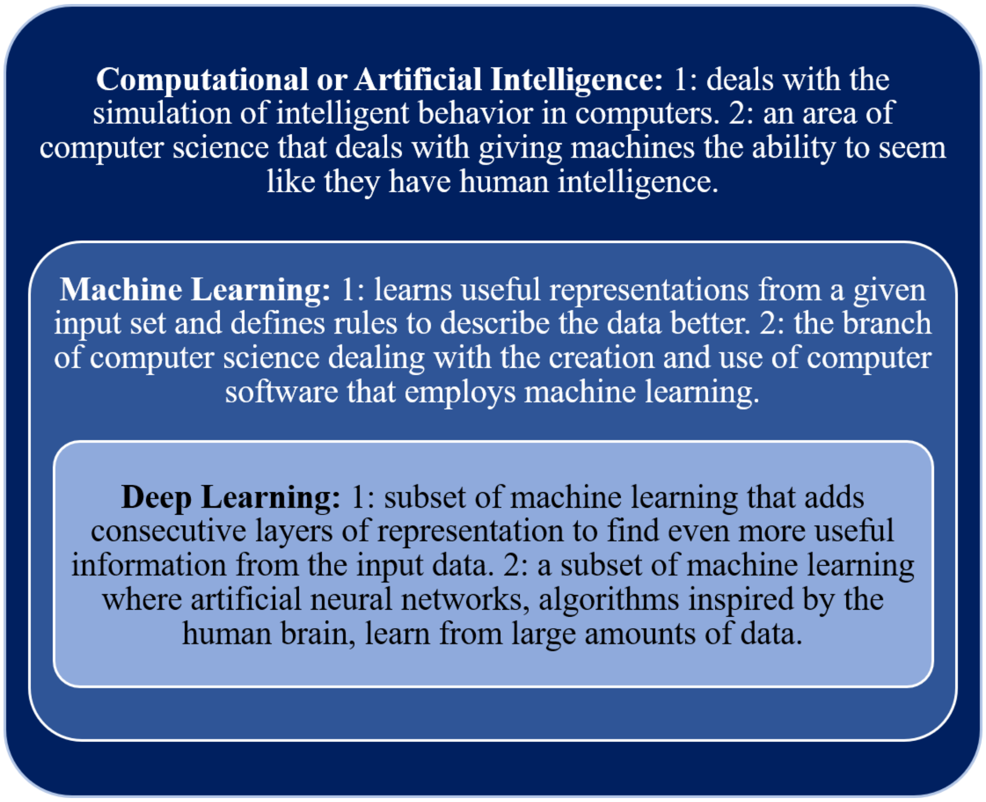


Figure 1: Relationship between computational or artificial intelligence, machine learning, and deep learning.

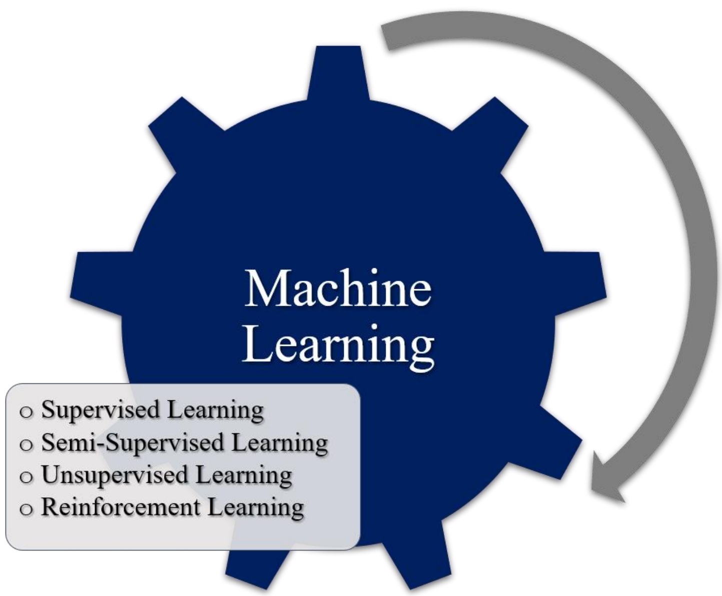


Figure 2: Types of Machine Learning.

Validation (the checking or proving of the validity or accuracy of something) employs a set of anemometer data to calculate the error during training and for monitoring the fit level of the ANN to the training data.

Generalization is the ability of the network to respond correctly to conditions never experienced before, i.e., the test dataset. As described in Haykin (1999), there are different possibilities for structuring an ANN based on the choices made for

i. *the number of hidden layers,*

ii. *the type of training,*

iii. *the architecture configurations,*

iv. *the type of neuron and transfer (activation) functions, and*

v. *the number of input/output parameters.*

To develop an ANN model, a set of input and output parameters are necessary. These sets are subdivided for use in the two different steps of network training and estimate validation. The correct selection of the predictors is crucial for the satisfactory performance of the model (Mori & Umezawa, 2009).

This work uses an approach to train the model for next-hour forecasting and then recursively infers the forecast for the following hours by applying artificial intelligence methods targeting short-term wind speed forecasting for the specified heights using AI. Figure 3 shows the supervised machine learning workflow.

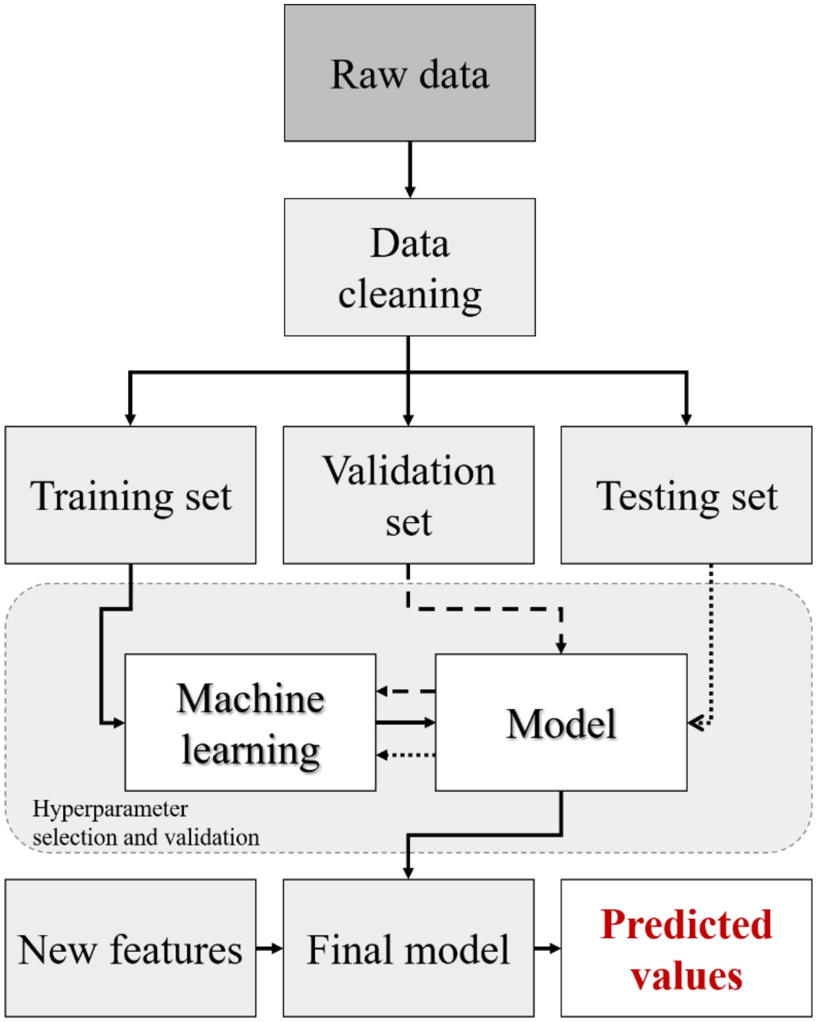


Figure 3: Supervised machine learning workflow.

The improvement of wind power technology has allowed the installation of turbines at high altitudes (100.0 m or higher), which requires knowledge of the wind potential at these heights. To validate the estimates and increase the number of wind farms installed in Uruguay, 100.80 m high anemometric towers were installed at locations with promising winds in Colonia Eulacio (Soriano is a department of Uruguay), which is the region considered in this study (Figure 4). According to Datum WGS84, the tower is located at 33°16' S, 57°31' W (Zucatelli et al., 2019a).

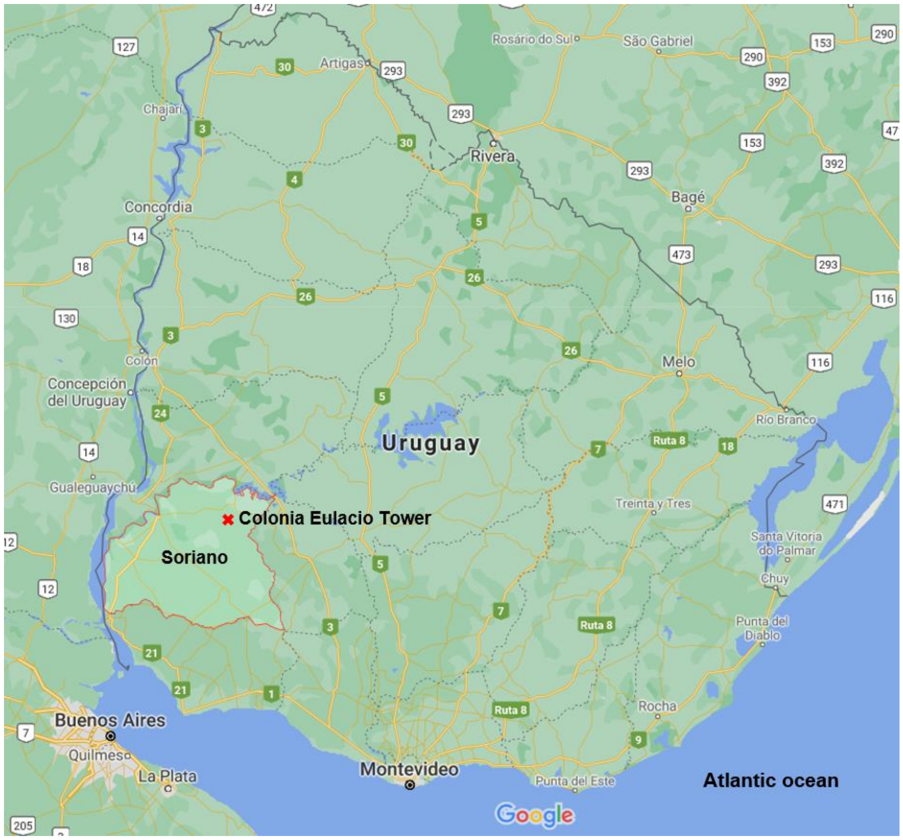


Figure 4: Colonia Eulacio Tower, Soriano department, Uruguay.

The measuring station used for this study is located in the southwestern region of Uruguay and consists of a 100.80 m high and 0.45 m wide triangular tower. The altitude of the installation location is approximately 100.0 m, and the location is surrounded by fields with plains. Thus, the location is characterized as a non-complex terrain. The station is owned by the *Administración Nacional de Usinas y Transmissiones Eléctricas*, or UTE. The UTE is a public energy sector company that works to make electric energy affordable in the country through the development of electricity generation, transmission, distribution, and commercialization well as the provision of advisory services and technical assistance in the areas of its specialty and annexes.

The computational intelligence procedure was coded and executed in Matlab together with Python by Google Colab, Google's free cloud service for artificial intelligence (AI) developers, and Keras, which follows best practices for reducing cognitive loads. Keras offers consistent and simple APIs, minimizes the number of user actions required for common use cases, and provides clear and actionable error messages. The MLP, RNN, GRU, and LSTM neural network configurations analyzed are listed in Table 1. In this study, the *fully connected* network structure was applied for RNN, GRU, and LSTM. The fully connected layers were defined using the Dense class.

Table 1. ANN configurations (config.) analyzed.

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

Each training and forecast simulation took, on average, 3 seconds for MLP, 8 minutes for RNN, 16 minutes for GRU, and 18 minutes for LSTM on a personal computer with 8 GB RAM.

The inputs for each ANN are:

i. *hour,*
ii. *day,*
iii. *month,*
iv. *year,*
v. *average hourly values of the wind speed,*
vi. *average hourly values of the wind direction, and*
vii. *average hourly values of the temperature.*

The insertion of these meteorological parameters as input data contributes to the efficient training and validation of each ANN. Some descriptive statistics for the wind speed at different heights are shown in Table 2.

Table 2. Wind speed: descriptive statistics.

Height [m]	Hourly average speed [m/s]	Standard deviation [m/s]
101.80	7.21	3.00
81.80	6.81	2.74
25.70	4.98	2.21
10.0	4.01	2.08

The ANN output is the predicted wind speed for the next hour. In view of the total hours registered in the anemometer (1 year of recorded data = 8,760 hours), the data were separated into training, validation, and test datasets at a ratio of 35:35:30 for all the ANNs. Each of the aforementioned ANN configurations was trained, validated, and tested to determine which was the most efficient for short-term (1 h to 12 h) wind speed prediction.

The activation functions, which define the outputs of the neurons in terms of their activity levels, that were inserted in this simulation are the:

i. *Sigmoidal function*, in the form of the *hyperbolic tangent function* (which is differentiable, nonlinear, continuous, and increasing), for the hidden layers in all configurations.
ii. *Linear function* for the output layer in MLP.
iii. *Softplus activation* function for the dense output layer in RNN, GRU, and LSTM. The Softplus is smooth and differentiable. Experiments show that deep neural networks with Softplus units achieve significant performance improvement.

To perform the forecasting, the ANN architecture that can achieve the best performance in the one-hour forecasting of the wind speed at each height (10.0 m, 25.70 m, 81.80 m, 101.80 m) is *first* identified. This forecasted wind speed value is then assigned as the input for the 2^{nd} hour of prediction, while the other input parameters (e.g. wind direction and air temperature) used at the start of the prediction are kept unchanged. The predicted wind speed for the *2*nd hour is calculated. This procedure, which is shown in Figure 5, is repeated until the *nth* hour of forecasting is reached.

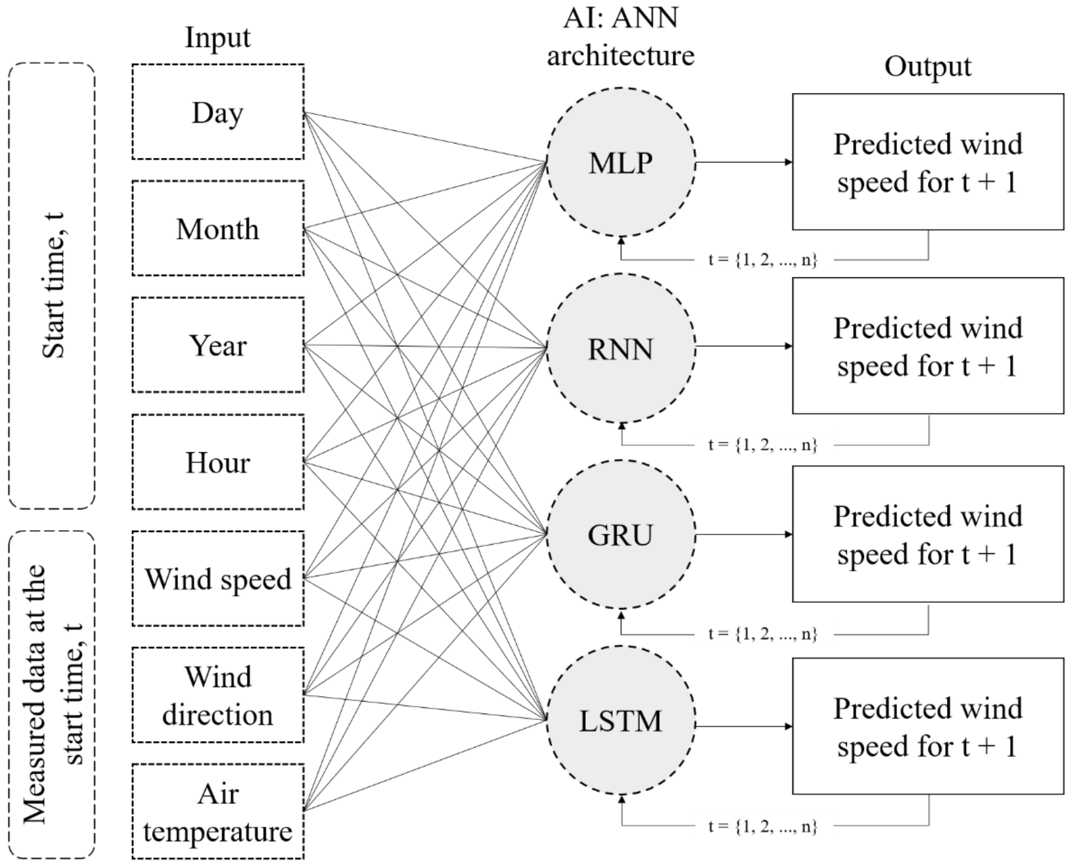


Figure 5: Workflow of the supervised machine learning AI wind speed forecasting procedure for 1 h to 12 h ahead of the start time.

As the forecasting horizon increases, the quality of the forecasted wind speed is expected to decrease. This is evaluated and discussed in section 3.

3. Numerical Results and Discussions

In this work, the statistical indicators employed to analyze the results are the mean absolute error (*MAE*), mean squared error (*MSE*), root-mean-square error (*RMSE*), mean absolute percentage error (*MAPE*), coefficient of determination (R^2 *or R-squared*), factor of two (*Fac2*), and Pearson's correlation coefficient (*r or Pearson's r*) as defined in Equations 1 to 8 respectively. An explanation of these statistical indicators is provided in [10, 11].

$$e_t = o_t - f_t \tag{1}$$

$$MAE = \frac{1}{n}\sum_{t=1}^{n}|e_t| \tag{2}$$

$$MSE = \frac{1}{n}\sum_{t=1}^{n} e_t^2 \tag{3}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{t=1}^{n} e_t^2} \tag{4}$$

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\frac{|e_t|}{o_t}x100\% \tag{5}$$

$$R^2 = \frac{\sum_{t=1}^{n}(f_t-\bar{o})^2}{\sum_{t=1}^{n}(o_t-\bar{o})^2} \tag{6}$$

$$r = \frac{\sum_{t=1}^{n}(o_t-\bar{o})(f_t-\bar{f})}{\sqrt{\sum_{t=1}^{n}(o_t-\bar{o})^2\sum_{t=1}^{n}(f_t-\bar{f})^2}} \tag{7}$$

$$Fac2 = \text{fraction of data [\%] for } 0.50 \le \left(\frac{f_t}{o_t}\right) \le 2.0 \tag{8}$$

where t is the time, n the number of samples, e_t the error, o_t the observed value, f_t the forecasted value, $\bar{o}$ the mean of all observed values, and $\bar{f}$ the mean of all forecasted values.

When connected and trained in multiple layers, an ANN model can represent any nonlinear function (McGovern et al., 2017). One advantage of an ANN model is that it can learn the relationship between complex nonlinear inputs and outputs (Quan et at., 2013). The best ANN configurations in this work are presented in Table 3. The aforementioned ANN architectures that were identified as the most efficient for the 1-hour forecast for each height were applied in the computational simulation to predict the wind speed for 2 h to 12 h ahead in Colonia Eulacio at all the heights tested. The best MLP architecture was described in Zucatelli et al. (2019a).

Table 3. The best ANN configurations.

ANN / heights	101.80 m	81.80 m	25.70 m	10.0 m
	Best ANN configurations			
MLP	7	4	7	4
RNN	1	3	7	5
GRU	7	6	6	5
LSTM	6	5	1	1

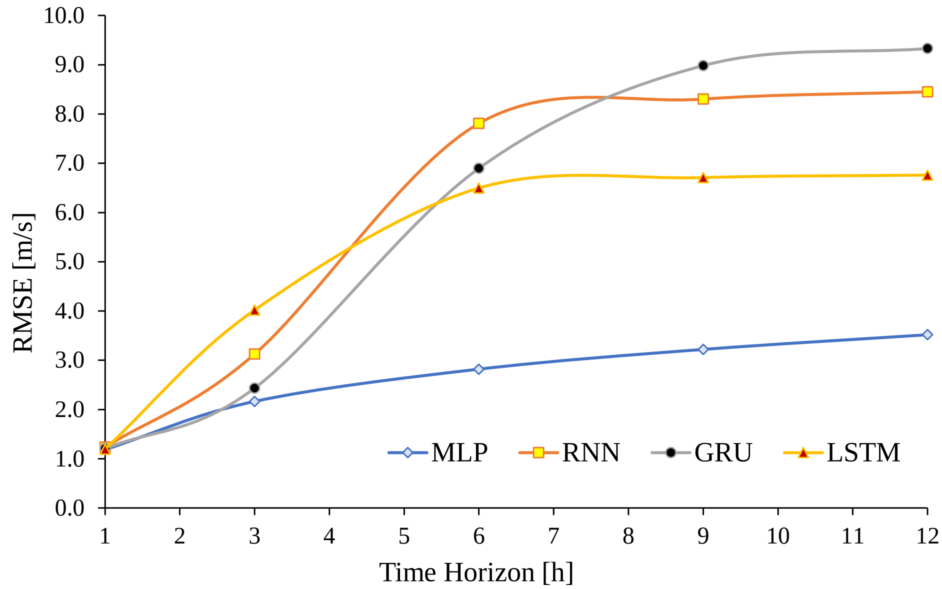
The statistical results for the 1 h to 12 h wind speed prediction at a height of 101.80 m are presented in Table 4. The lowest values of the MAE, MSE, RMSE, and MAPE, as well as the highest Pearson's correlation coefficient and R^2 values, were recorded for the 1-hour forecast for all the analyzed heights (10.0 m, 25.70 m, 81.80 m, and 101.80 m). The mean R^2 and Pearson's r for the 1-hour wind speed forecasting are 0.843 and 0.918, respectively. The lowest MAPE value is 15.84% for the height of 101.80 m and prediction horizon of 1 hour.

The results showed in Table 4 indicate that as the wind speed prediction load increases, the quality of the ANN forecasting output data decreases. Thus, a longer prediction time yields a larger error. As explained in the previous section, these results are expected as the adopted procedure uses the input data from the start of the prediction in addition to the wind speed computed for each forecasted hour to predict the wind speed for the *nth* hour, leading to accumulated errors. This result is consistent with the literature, e.g. Zucatelli et al. (2019a); Zucatelli et al. (2019b); Kusiak et al. (2009); Blonbou (2011); Carpinone et al. (2015); Filik and Filik (2017). Figure 6 presents a graphical comparison of the RMSE [m/s] and Pearson coefficients for different ANN models at 101.80 m. The graph shows that as the prediction horizon [h] increases, the RMSE increases, indicating that the error between the actual and predicted values increases.

Table 4. Performance indices of forecasting results obtained by different models on the case study for the height of 101.80 m.

MLP					
Prediction Horizon [h]	1	3	6	9	12
MAE [m/s]	0.89	1.67	2.24	2.59	2.87
MSE [m^2/s^2]	1.40	4.68	7.95	10.3	12.38
RMSE [m/s]	1.18	2.16	2.82	3.22	3.51
Pearson	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 [m/s]	0.93	2.64	7.29	7.78	7.94
MSE [m^2/s^2]	1.53	9.77	60.99	68.97	71.43
RMSE [m/s]	1.23	3.12	7.81	8.30	8.45
Pearson	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 [m/s]	0.91	1.96	6.41	8.49	8.85
MSE [m^2/s^2]	1.45	5.92	47.56	80.69	87.04
RMSE [m/s]	1.20	2.43	6.89	8.98	9.33
Pearson	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 [m/s]	0.89	3.45	5.85	6.08	6.13
MSE [m^2/s^2]	1.43	16.15	42.22	45.03	45.71
RMSE [m/s]	1.19	4.02	6.49	6.71	6.76
Pearson	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

a)



b)

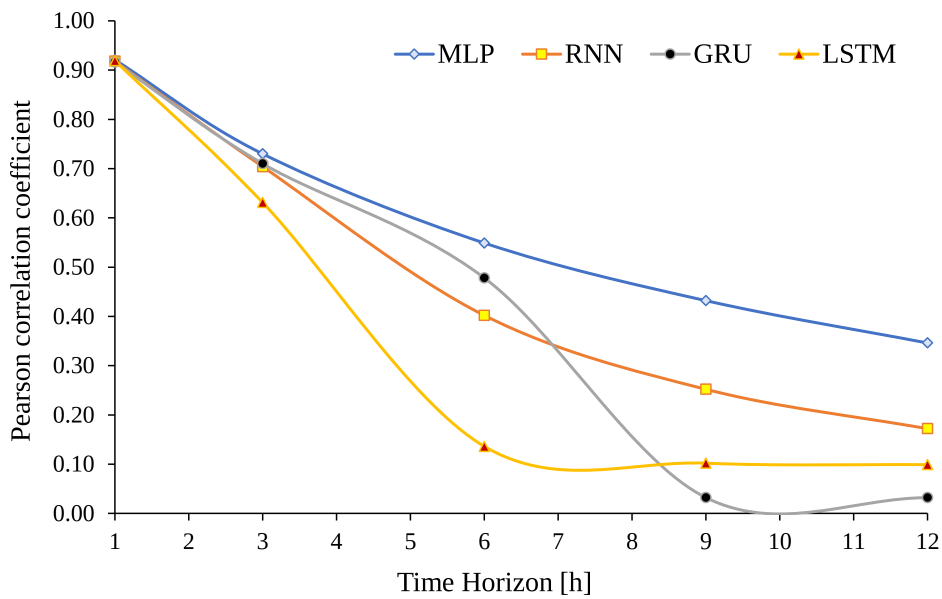


Figure 6: Graphical comparison of a) the RMSE [m/s] and b) Pearson coefficient at different prediction horizons for different ANN models (height: 101.80 m).

Nowcasting refers to short lead-time weather forecasts. The U.S. National Weather Service specifies a lead-time of zero to three hours, although forecasts of up to six hours may also be called nowcasts by some agencies. Nowcasting is usually performed with techniques that differ significantly from the usual numerical weather prediction models (Kuikka, 2009; Zucatelli et al., 2019e). Figure 7 shows a comparison of the statistical results for the root mean squared error [m/s] at different heights for the wind speed prediction at 6 h (which is important in nowcasting to short lead-time wind speed forecasting) using different ANNs. The best results were recorded for MLP followed by LSTM.

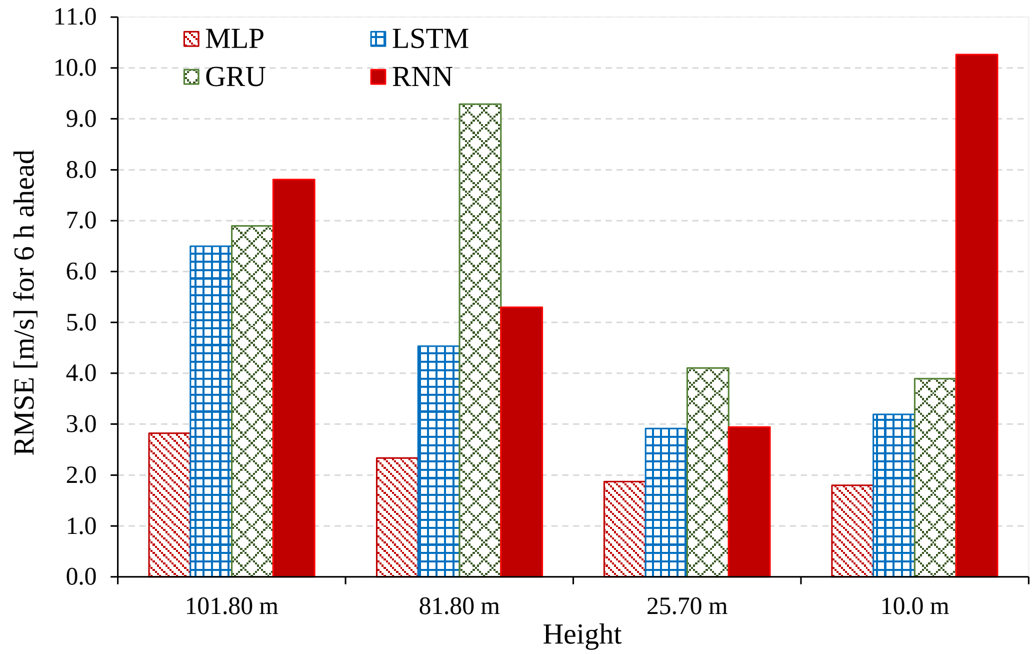


Figure 7: RMSE [m/s] for 6 h ahead using MLP, RNN, GRU, and LSTM at different heights.

Figure 8 shows the dispersion between the anemometer and predicted wind speed 6 h ahead using MLP (i.e. nowcasting). Figures 9 a), b), and c) present a comparison of the results for the 6 h ANN wind speed forecasted (nowcasting) through the MLP designed in Zucatelli et al. (2019a) with the actual data recorded at Colonia Eulacio at the anemometer height of 101.80 m. The ratio between the wind speed predicted by the ANN model and that measured by the anemometer is also plotted with respect to the time and the measured wind speed. The middle lines in the plots indicate one-to-one correspondence, and the outer lines indicate differences by a *factor of two (Fac2)*.

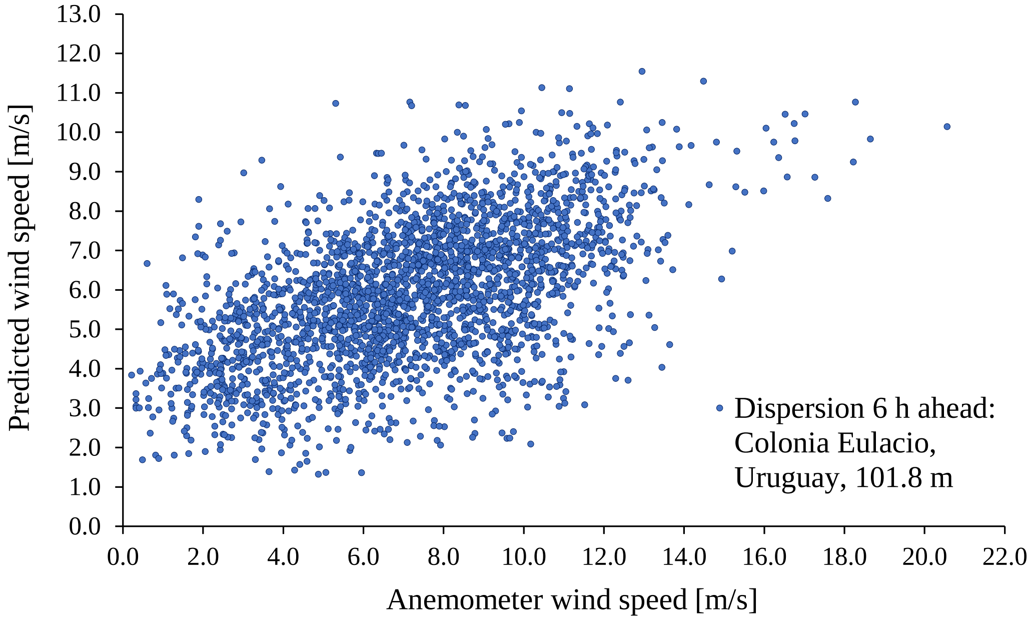
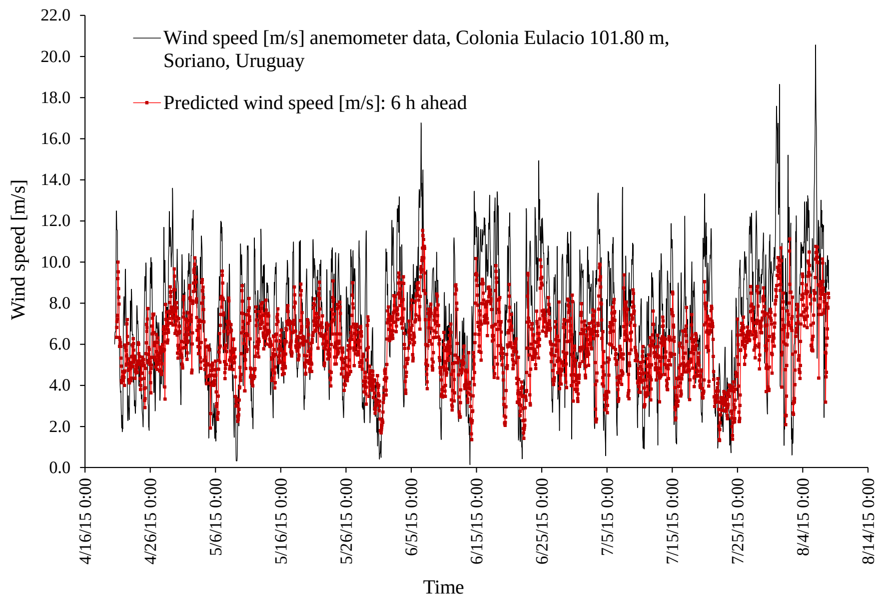
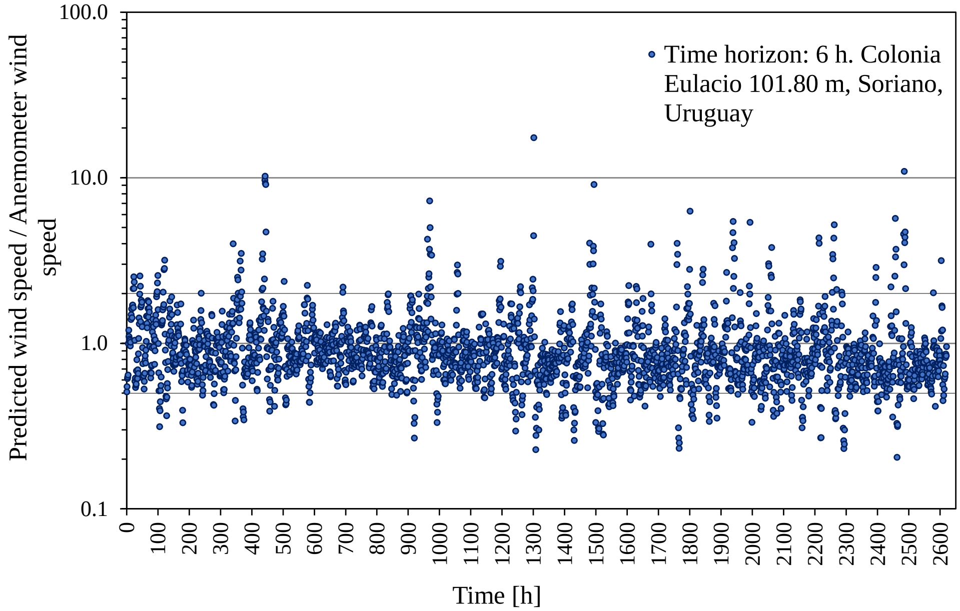


Figure 8: Dispersion results for forecast 6 h ahead at 101.80 m.

a)



b)



c)

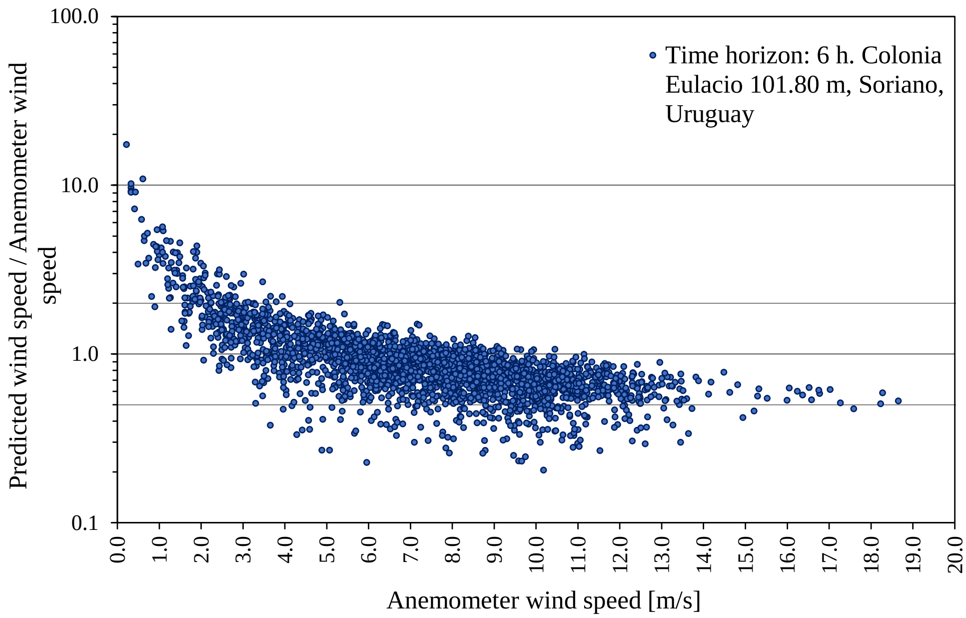


Figure 9: Short-term wind speed prediction for 6 h ahead (nowcasting): a) The results of six-step predictions of the wind speed series [m/s]; b) Comparison of *Fac2* versus time [h], and c) Comparison of *Fac2* versus anemometer wind speed [m/s].

The degradation of the forecast can also be seen from the movement of the predicted curve away from the actual curve as the forecast horizon increases. Table 5 presents the percentage of the predicted wind speeds that match the actual wind speed within a factor of two. The MLP and LSTM models are the only models that maintained results within the *factor of two* (i.e *Fac2*) above 58% of the forecasts.

Table 5. Percentage of the forecasts within a factor of two (height: 101.80 m).

ANN model	Prediction horizon	Percentage of the forecasts within a factor of two, *Fac2*
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 10 indicate that on average, the MLP ANN has better results than the persistence model for a prediction horizon of 1 h.

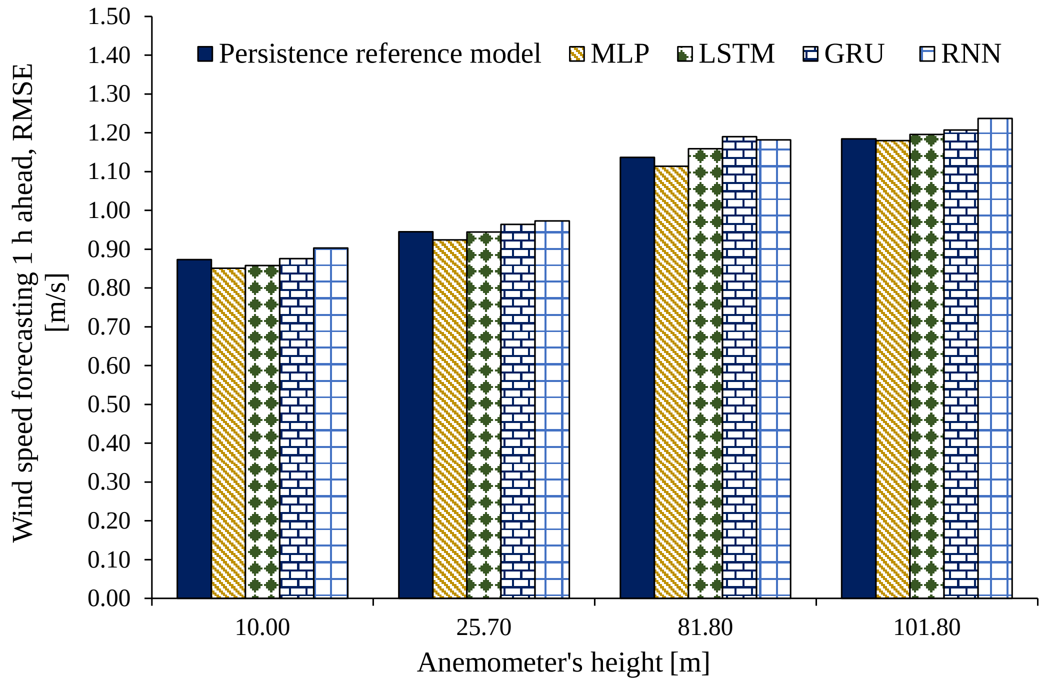


Figure 10: Comparison between the ANN models and the persistence reference model for wind speed forecasting 1 h ahead.

The investigation of mechanisms that aid the short-term wind speed forecasting for 1 h to 12 h ahead as performed in this study for energy generation in wind farms has been critical for ensuring the proper functioning of traditional energy systems. Accurate prediction of the short-term wind speed output helps system operators to

i. *reduce the operational costs of the power system,*
ii. *mitigate the adverse effects of wind power fluctuations,*
iii. *adjust scheduling plans in a timely manner,*
iv. *make correct decisions, and*
v. *reduce standby capacity.*

Wind energy has become a major source of electricity supply in Uruguay and around the world. The large contribution of wind energy to the reliable operation of the electric power network today makes the application of supervised machine learning AI to wind speed forecasting very important. Wind energy has characteristics that differ from electricity generation powered by coal, petroleum, nuclear, and natural gas. Because wind generation is driven by meteorological processes, it is intrinsically variable and has real-time fluctuations on the time scale ranging from minute-to-minute fluctuations to yearly variations affecting long-term planning for utility operations. These characteristics can require changes in system operational practices and the potential addition of flexibility reserves to help manage increased variability and uncertainty from wind energy.

4. Conclusions

The application of computational intelligence (supervised machine learning) is a viable alternative for the forecasting of wind speed and thus wind energy generation mainly because of the low computational cost. However, an ANN configuration that is appropriate for the forecasting must be selected, and the data fed to the model must be quantitatively and qualitatively analyzed because these variables directly impact the prediction results. This research is relevant because it is a first step in the application of the MLP, RNN, GRU, and LSTM models to wind speed forecasting. There have been no previous studies on the application of computational intelligence using supervised machine learning and deep learning through such ANNs for this region.

The statistical results for the prediction horizons of 1 h to 12 h for each anemometric height exhibit predictable behavior similar to that for short time ranges. These results are novel because no other studies have used these computational models to predict the wind speed in Uruguay. The MLP and LSTM models are adequate for wind speed forecasting at different heights. From the analysis, it was found that the MLP model is superior to the other neural network models because it can achieve a relatively lower prediction error. The MLP approach introduced here uses a differentiated process of forecasting based on inference.

The surprising result is that the simplest model architecture of a MLP (using the Levenberg–Marquardt algorithm, also known as the damped least-squares method) with only two hidden layers containing one neuron in each layer gives the best performance among the considered architectures. This result suggests that deeper neural network architectures (deep learning), ensemble other models, may achieve higher performance. The 1 h to 6 h forecasts are particularly accurate (i.e. nowcasting). As the forecast time increased, the accuracy of the results decreased, as expected. However, this degradation does not render the forecasting results for longer prediction horizons useless. The proposed technique can still produce satisfactory short-term wind speed forecasts of up to 12 h with low computational costs to help wind-farm operators with decision making.

This study contributes to the scientific community considering the interest of private companies and UTE in the energy sector by providing wind speed prediction information for Uruguay. Future work can study the application of wavelets decomposition to weather data and deep learning technology (LSTM, GRU, and CNN or convolutional neural networks) for wind speed and wind power forecasting. Wind ramps and longer forecasting horizons are also future subjects for research.

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