A novel strategy for wind power forecast through neural networks: Applications to the Uruguayan electricity system

Guillermo Flieller
DNC
ADME
Montevideo, Uruguay
gflieller@adme.com.uy

Alfredo Solari
Facultad de Ingeniería
Universidad de la República
Montevideo, Uruguay
alfredo.solari@fing.edu.uy

Rafael Bruno
DNC
ADME
Montevideo, Uruguay
rbruno@adme.com.uy

Ruben Chaer
DNC
ADME
Montevideo, Uruguay
rchaer@adme.com.uy

***Abstract*—In systems with a high penetration of wind power generation, the precision of the forecasts is a critical input for the electricity dispatch planning. In this paper, we present the methodology that has been used to implement a complete update of the wind power forecast model in Uruguay. The new model increases the precision of the forecasts both in low and high power scenarios. It allows to perform a more efficient short-term electricity dispatch, improving the resource valuation, the inter-systems energy exchanges and the prevision of the wholesale electricity market spot price. According to the simulations performed, the new model increase the precision of wind power forecasts between 7% and 32%. The model is on its production phase and their results can be accessed through pronos.adme.com.uy/svg and latorrex.adme.com.uy/vates.**

***Index Terms*—renewable energy systems, forecasting, wind energy, , neural networks, wind turbine power curve.**

I. Introduction

A. Background

The Uruguayan interconnected electricity system has a total installed capacity of around 4900 MW, with over 1500 MW corresponding to hydroelectric power and over 1500 MW to wind power. From 2018 to 2022, the participation of wind energy in the total electricity mix ranged from 33.6% to as high as 45%.

The Independent System Operator (ADME) manages the economic dispatch of the Uruguayan electricity market, among other objectives. To do so, ADME relies on power production forecasts for the most crucial variables.

To understand the relevance of wind power resource availability predictions, the following hypothesis must be taken into account. First, the variables involved in hydraulic resource availability have a long-term perspective, spanning several years [1], whereas wind speed exhibits much higher-frequency patterns on a daily and weekly basis [2]. Second, wind power generation in Uruguay operates under take-or-pay contracts, which means it is not considered as an additional cost in a marginalist approach to resource optimization.

ADME: Administración del Mercado Eléctrico, Uruguay.

B. Motivation

In this context, the most significant input to the determination of the cost-to-go, considering that the operation of the system is optimized through Stochastic Dynamic Programming [3], are the mid and long-term (ranging from three months to three years) estimates of available hydroelectric power.

A precise forecast of the short-term wind power, provides useful information for the decisions regarding the startup and shutdown process of some thermal generation units, which take a considerable time to complete. Such forecasts reduce the error of the cost-to-go function, allowing to optimize the international energy exchanges. The forecasts are a critical input for the energy dispatch, reducing risks and increasing the efficiency of the system.

A deviation between wind power measure and forecast was observed on a frequent basis, which motivated an investigation to determine the cause. The deviation was mainly observed on the upper and lower bounds, which led to underestimation of high power and overestimation of low power.

Based on that observation, an exploratory analysis of the wind speed forecast was performed, determining that there were systematic biases between wind speed measures and forecasts.

C. Objectives

In this work, we present a novel strategy for the forecasting of short-term wind power, and the results obtained from this new strategy. This forecasting strategy has already been implemented and is currently being used by ADME. These are a significant upgrade from the previous models and have increased forecast precision in conditions of both high and low wind power [4] [5].

II. Methodology

Regarding the last observation, we decided to generate a two-stage model. The first stage is called Wind-Wind Correction Model (WWCM), and it implements a artificial neural network (ANN) to correct the wind speed forecast. The second stage is called Wind-Power Conversion Model (WPCM), and it consists of fitting a sigmoid-like exponential function to convert the wind speed forecast to electrical power forecast.

The model was trained using wind speed, wind direction and solar radiation as inputs, considering the information available for 2019, 2020 and 2021, both from real measurements as well as from previous forecasting models. The curve is also adjusted with the same data, and validated with same validation set as the ANN. Each wind farm was calibrated independently, which means that more than 35 different models were implemented. Fig. 1 shows the general diagram of the model implemented.

A. Data

The data used for this study included forecasts and measures at 35 wind farms in Uruguay from January 2019 to February 2022. Measured variables were electric power production, wind speed and direction. Forecasts variables were global horizontal irradiance, wind speed and direction. The source of the forecasts considered was the package *wind energy* of the company *MeteoBlue* [6].

From the exploratory analysis of the data, some patterns in abnormal data and outliers were detected. Most of those were assigned to constant power values on a wide ranges of wind speed, which can be explained due to uninformed maintenance or dispatch curtailments. Other sources of unreliable data include instrumental or communication failures. In order to detect and remove the abnormal data and outliers, the raw data must be filtered.

During the filtering process implemented, the data is sorted in groups by power (MW), calculating the mean (μ) and standard deviation (σ) for each group. Values outside the $[\mu \pm 2\sigma]$ range are discarded. This process must be done in an iterative manner, until the data set obtained is considered acceptable to begin with the calibration of the models. Fig. 2 shows an example of the data before and after applying the filter.

B. Two-Stage Model

During design, a single-stage model that converts directly the wind speed forecast to electric power was considered but dismissed due to the inconvenience given by calibrating using non-measured data.

That is, electric power measure would be used as the output from a wind speed forecast input, even if that speed forecasted could be different to the actual speed. This kind of schema tends to have a pathological behaviour, where predictions avoid extreme values. Furthermore, any methodological change performed by the company that provides the meteorological forecasts, would imply a complete recalibration of the whole model, for all the wind farms.

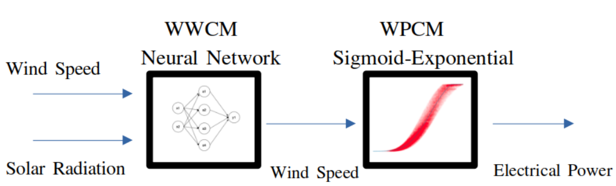
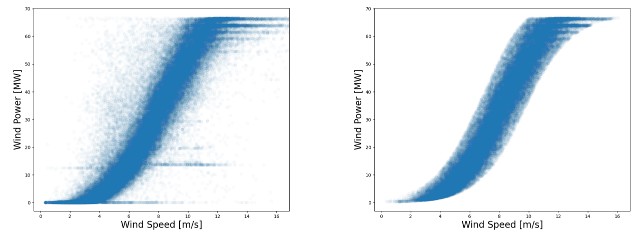


Fig. 1: Global diagram of the model implemented



(a) Before filtering (b) After filtering

Fig. 2: Data cleansing

Therefore, the aforementioned two-stage model was conceived. At stage one, a wind speed correction is performed, and at stage two, power is predicted using the wind speed obtained from stage one.

Here, a remarkable advantage arises from building a robust wind-to-power model of each wind farm as a whole, which is independent of the source of wind speed forecast and its provider.

C. Wind-Wind Correction Model

The Wind-Wind Correction Model (WWCM) aims to correct the bias detected in the forecasted wind velocity. On an initial stage, four inputs were considered for the ANN: wind speed, solar radiation (GHI), temperature and air density. A similar approach was studied on [7], where ANN were evaluated for the wind-to-power turbine modelling. During the tests performed, it was determined that the variables Temperature and Air Density had almost no effect on the results. Therefore, those variables were not considered in the final version of the model.

In this implementation, the WWCM includes 72 *directional* networks, where each one corresponds to a 7° sector of wind direction, and the sectors are equally spaced 5°. Other implementations could be done with different spacing and different overlap. For the training of the network, the forecasted wind speed and solar radiation are the inputs, and the measured wind speed is considered as ground truth.

The WWCM training is divided in two steps. As the first step, an initial network is trained using data from all the directions. The parameters obtained from that initial training are used as seeds for the second step. In the second step, the *directional* individual networks are trained using data only from the corresponding wind directions.

During the second step, a regularization parameter must be used to penalise the differences between the weights and biases of adjacent networks. This regularization solves the problems that arise when a sector has a small amount of samples. On

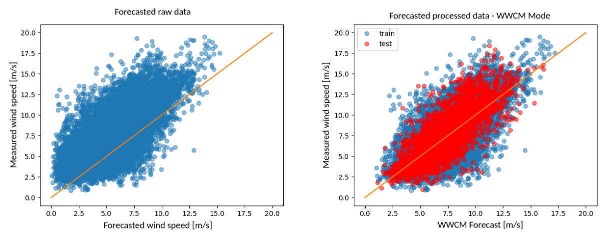


Fig. 3: Wind-Wind Correction Model

each wind farm, there is a prevailing wind direction, and the position of the wind turbines is determined based on that direction. Therefore, having an imbalanced amount of samples along the direction sectors is intrinsic to behaviour of wind and the wind farms characteristics.

Fig. 3 and table I, show the improvement achieved after processing the raw data through the WWCM.

TABLE I: WWCM against measurements - Residual Variance

Model	**Test Data**	**Overall Data**
Raw Forecast	58.4	58.4
Global Network	3.14	3.54
Directional Network	2.72	3.97

1) Regularization on WWCM: In order to prevent overfitting, a regularization technique is used. In this case, is implemented through a parameter that penalises the differences between adjacent networks. The aim of this penalty is to avoid issues that arise when a network is trained using a small dataset, which is an intrinsic problem when working with wind speed; every location has a prevailing wind direction and thus there are directions that are secondary and have a small dataset. An example of this problem is shown in Fig. 4. It shows a 6-year dataset, with directions that have more than 12000 samples and directions with nearly 1000. Therefore, there is a 12-times difference in the number of samples between the most and the least frequent direction.

Using shallow neural networks and using few input parameters act as a regularization on its own. The results shown correspond to an implementation with a one neuron network for each direction, since the deviation between the wind forecasts and the measures were considered linear. As is, the method has no restrictions with the architecture of the neural network to be used.

D. Wind-Power Conversion Model

The Wind-Power Conversion Model (WPCM) developed is an electro-mechanical representation of the overall response of the of each wind farm to the wind speed and direction, as the sum of the production of all its turbines. It consists on a set of sigmoid-like exponential function, bounded between 0 MW and the nominal power of the wind farm. The model is calibrated for each wind farm independently, and for each wind direction sector corresponding to the ones in WWCM. The function used for the calibration is shown on (1). The

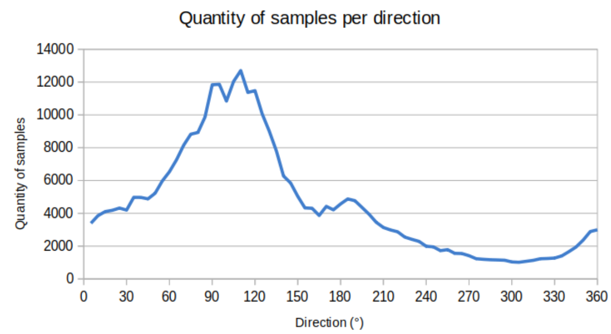


Fig. 4: Example of amount of samples per direction for one of the studied wind farms.

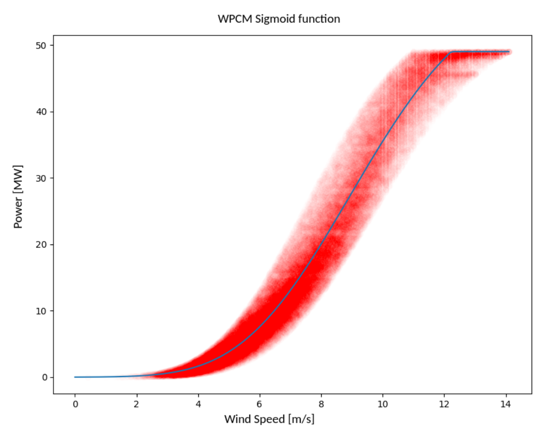


Fig. 5: Wind-Power Conversion Model

function is similar to several studied by Wang et al. [8], it has several advantages over classical sigmoid including that it can generalize a wide range of functions.

An example of the wind to power curve obtained for one of the studied wind farms is presented in Fig. 5.

$$P(v) = A \cdot e^{-\frac{(v-v_o)^4}{B}} - C \tag{1}$$

Where v stands for wind velocity and P for power. The other parameters are calculated using the least squares method.

III. Results

A. Comparison to previous model

Table II shows the difference between the previous and the new model, using the Mean Absolute Error as the comparison metric.

TABLE II: Mean Absolute Error of the models evaluated

	Overall	**High Power**	**Low Power**
Previous Model	151 MWh	89 MWh	157 MWh
New Model	110 MWh	83 MWh	106 MWh
Improvement	27 %	7 %	32 %

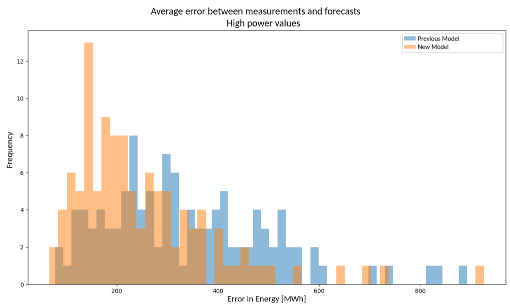


Fig. 6: Error between forecasts and measurements - High power values

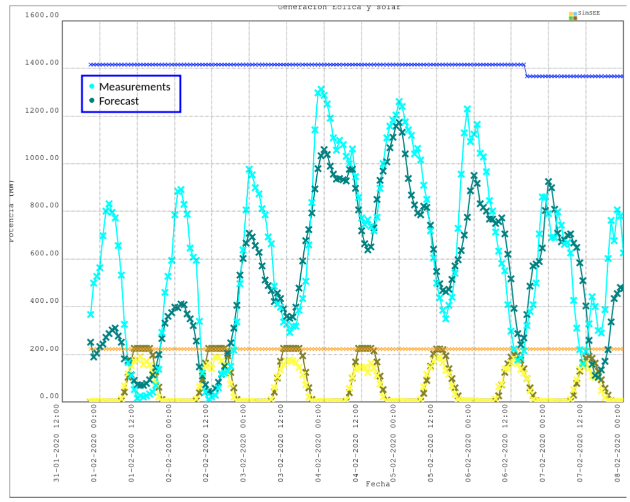
Fig. 6 shows the histogram of the error for both the previous and the current model. As it can be seen, the orange (current) shows a displacement to the left, with respect to the blue (previous); which means that the error decreases.

A qualitative comparison can be seen in Fig. 7, which shows the outputs of the models for the same week.

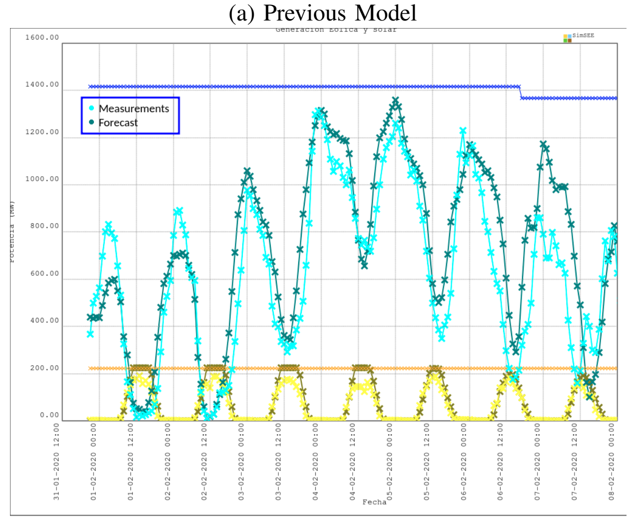
B. Applied to the weekly dispatch programming

The methodology presented in this paper is currently being used by ADME as source of forecasts for the availability of wind power resources for the weekly programming of electricity dispatch. For this purpose, ADME runs in an hourly manner an update an optimization of the dispatch for the the week ahead using the software Vates [4].

Subplots on Fig. 8 show the electricity dispatch estimated by Vates and the executed dispatch for the week of the 8th of July of 2023 respectively.



(a) Previous Model



(b) New model

Fig. 7: Comparison between new and previous model

IV. Conclusion

In this paper, novel methodology for wind power forecasting is introduced. The results of the implementation presented show remarkable performance improvements over the classic sigmoid fitting approach, achieveing 27% reduction in mean absolute error (MAE) for the Uruguayan interconnected system, outperforming the classic method by 7% in the low power step and 32% in the high power step.

A key advantage of the proposed methodology is its computational efficiency compared to other methods, such as deep neural networks, making it a more resource-efficient solution for wind power forecasting.

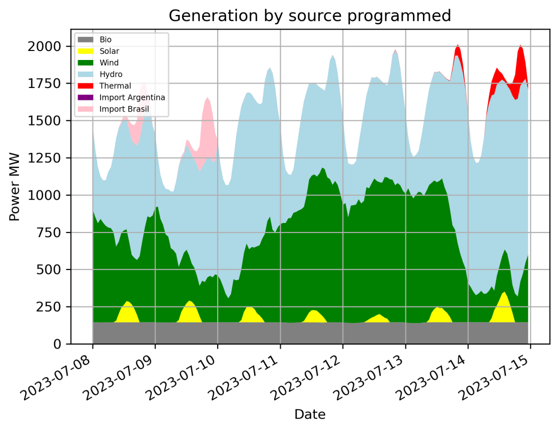
Furthermore, this methodology has shown effectiveness to predict events near the power bounds, whether they are close to zero or the maximum power capacity. This ability to forecast events close to the bounds with precision is a valuable asset for efficient power management and decision-making.

The uneven distribution is intrinsic to the problem. To address this, equal-sized bins in degrees were used. This approach implies extrapolating the parameters of the most densely populated bins to less populated ones, assuming similar behavior. Therefore, this method relies heavily on the hypothesis that the least populated bins behave like the most populated ones. If this hypothesis is not met, then the model would lead to imprecise results.

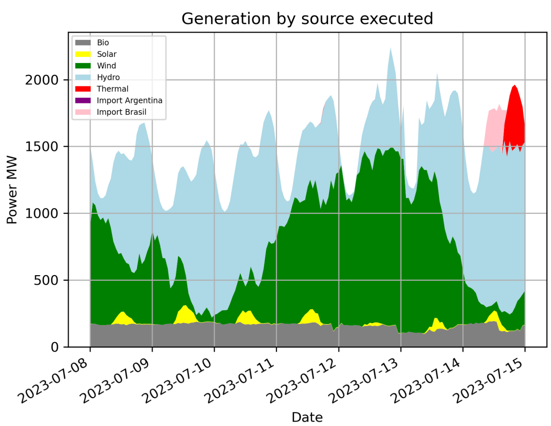
Finally, the proposed methodology exhibits a risk-adverse characteristic given by the two-stages algorithm. By employing a two-step approach, the methodology segregates one model for correcting the meteorological forecast information and another for the wind farm model. This segregation allows users to maintain the same model for the wind-speed vs wind-power curve, even when changing meteorological services, just by training the first stage again. The capacity to interchange meteorological services without modifying the underlying wind speed and power curve model ensures greater stability and adaptability in wind power forecasting, reducing uncertainties and enhancing the system's overall reliability.

V. Future works

Considering the notable advancements made in the current work related to short-term electricity dispatch, it would be interesting to continue expanding the application of this model



(a) Programmed generation



(b) Executed generation

Fig. 8: Comparison between programmed and executed dispatch

to the other programming tools utilized by ADME, especially in the context of mid-term dispatch planning.

After validating the neural networks' ability to rectify erroneous data, it is might be possible to advance the initial phase of the methodology, with a specific focus on conducting tests with more complex network architectures.

Despite not being a direct component of the objectives for a potential follow-up project, it is considered important to implement stricter data quality control measures for wind farm operators. This is because a significant portion of the data that was removed during the data cleansing process stemmed from instrumental or communication failures.

Disclaimer

The content of this article is entirely the responsibility of its authors, and does not necessarily reflect the position of the institutions of which they are part of.

References

[1] G. Casaravilla and R. Chaer, "Energía hidroeléctrica en uruguay: país lluvioso con sequías.," *Informe elaborado por docentes e investigadores del Grupo Energía Eléctrica del Departamento de Potencia-IIE-FIng-UdelaR, Jul. 2020., pp. 1-3*, 2020.

[2] T. Ackermann, *Wind power in power systems, 2nd Edition*. John Wiley & Sons, 2012.

[3] R. Chaer and P. Monzón, "Stability conditions for a stochastic dynamic optimizer for optimal dispatch policies in power systems with hydro-electrical generation," in *2008 IEEE/PES Transmission and Distribution Conference and Exposition: Latin America*, pp. 1–5, IEEE, 2008.

[4] X. Caporale, D. Vallejo, and R. Chaer, "Vates. optimal operation of power systems with consideration of production forecasts in systems with high wind and solar penetration," *Renewable Energy and Power Quality Journal*, vol. 16, pp. 608–612, 2018.

[5] X. Caporale, F. B. Galusso, and R. Chaer, "Incorporation of forecasts to the optimal operation of dynamic systems using stochastic cegh models," in *2018 IEEE 9th Power, Instrumentation and Measurement Meeting (EPIM)*, pp. 1–4, IEEE, 2018.

[6] Meteoblue, "Wind energy weather data & forecast," 2023. https://content.meteoblue.com/en/business-solutions/sectors/wind-energy [Accessed: (07/08/2023)].

[7] F. Pelletier, C. Masson, and A. Tahan, "Wind turbine power curve modelling using artificial neural network," *Renewable Energy*, vol. 89, pp. 207–214, 2016.

[8] Y. Wang, Q. Hu, L. Li, A. M. Foley, and D. Srinivasan, "Approaches to wind power curve modeling: A review and discussion," *Renewable and Sustainable Energy Reviews*, vol. 116, p. 109422, 2019.