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Operational wind power forecast with ANN GFS-WRF ensembles members.

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SUMMARY:

Wind power forecast are particularly relevant to wind engineering and it is of interest to develop a forecasting tool for wind energy management for systems such as Uruguay's, which has a wind power participation of 36% total electricity generation in 2022 . In the present work, we assess the performance of wind power forecast of 37 wind farms with a total installed capacity power 1457 *MW* based in Artificial Neural Network (ANN) WRF-GFS, applied in an operational configuration. Ensemble Prediction Systems (EPS) are often used to quantify the uncertainty associated with forecasts as well as the most likely outcome. Instead of running one operational model once (a deterministic forecast), the model is run many times from very slightly different initial conditions. We propose a methodology of training ANN forecast tool with control member of GFS-WRF, with operational forecast model with full 30 ensemble members GFSENS. The focus of the paper is to present the results of 24 hours to 72 hours time horizon forecasts.

Keywords: wind power forecast, WRF, ensemble, ANN

1. INTRODUCTION

Electric system must always ensure the balance between electricity production and consumption. Currently, a safe and robust operation needs highly accurate forecasts of power production. With increasing participation of renewable power systems, the role of forecast and its accuracy becomes more relevant Couto et al., 2021. Wind power forecast are crucial particularly in country's such as Uruguay's in which wind power participation of 36% total electricity generation fed into the national interconnected system, UTE, 2022. Considering a time horizon of a day ahead forecast and greater, it is need a numerical model of the atmosphere circulation, Widén et al., 2015 provides an overview and comparison of forecasting models, taking account the time horizon. Mesoscale models such us WRF Skamarock and co-authors, 2008 can improve the skill by increasing horizontal resolution that can be implemented. More relevant wind fluctuation that can impact in power production are gust, Gutiérrez and Fovell, 2018. Recent works present wind power forecast models, from input of atmosphere numerical simulation (mesoscale numerical models) combined with Artificial Neural Network (ANN) with focus in day a head and greater time horizon Donadio et al., 2021; Groch and Vermeulen, 2022; Tan et al., 2021. For a sustainable integration of wind power into the electricity grid, a precise prediction method is required. Ensemble Prediction

Systems (EPS) are often used to quantify the uncertainty associated with forecasts as well as the most likely outcome. Instead of running one operational model once (a deterministic forecast), the model is run many times from very slightly different initial conditions, WMO, 2012. In Berner et al., 2011 it is shown WRF ensemble members running with focus in improve forecast uncertain. Atmospheric ensembles have proven to be very useful for power system operators, and wind farm managers. Heinermann and Kramer, 2016, investigate the use of machine learning ensembles for wind power prediction.

The focus of the paper is to present the results of 24 hours to 72 hours time horizon forecasts of an operational ensemble forecast GFSENS (30 operational members with perturbation in initial conditions of GFS) WRF-ARW with 12km spatial resolution, with ANN power forecast model.

2. WIND FARMS AND WRF DOMAIN

The full wind power capacity located in Uruguay were considered for this study, 37 wind farms with a total installed capacity power 1457 MW. The input data for the WRF numerical model were from the GFS (Global Forecast System), GFS, 2022. These data from the GFS control member were used as input to the WRF-ARW model. WRF simulations used version 4.3 and employed one domain of 12 km horizontal of resolution (Fig. 1).

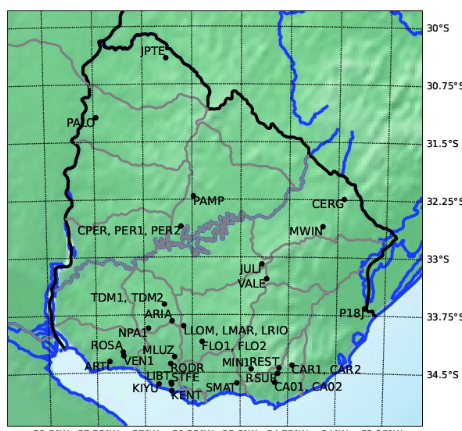

Figure 1. Wind farms location with code reference for all 37 locations with a full installed capacity of 1457 MW.

All simulations utilized 37 vertical layers. Common model physics selections include the RRTM longwave Mlawer et al., 1997 and Dudhia shortwave Lacis and Hansen, 1974; Stephens, 1978 radiation schemes, Lin microphysics Yuh-Lang Lin, 1983, and the Noah land surface model Chen and Dudhia, 2001 . The Kain–Fritsch Kain, 2004; Kain and Fritsch, 1990 cumulus scheme, and PBL planetary boundary layers scheme Mellor-Yamada-Janjic (Eta) TKE scheme, Mellor and Yamada, 1974, 1982.

3. GFS-WRF-ANN POWER FORECAST MODEL

The ANN model takes as input atmospheric variables from WRF output, wind speed at 100 meters, air density, air temperature, vertical gradient of temperature, maximum velocity in 1000 m, vertical level of maxi mun velocity. Two other variables are used as input, which are solar declination and "fuzzy hour". Solar declination is added to incorporate seasonality, the "fuzzy hours" Ross, 2010 incorporate atmospheric stability. Solar declination is defined as the angle formed by the Earth-Sun line with the equatorial plane of the Earth Spencer, 1971. The "fuzzy hour" are variables [0 to 1] with daily variation for discrimination of night and day.

Based on supervised learning, we implement backpropagation method, D. Rumelhart, 1986 for training the ANN, where the input variables of the model were introduced together with the wind power data for the learning process, average hourly power data of each wind farm were considered forecast variable (target). Three layers were used in the neural network (an input layer, a hidden layer and an output layer), where the hidden layer had 100 neurons and the output layer had 1 neuron. Data from 1/9/2018 to 1/9/2020 was used for training, data for test validation from 2/9/2020 to 31/7/2022.

4. OPERATIONAL FORECAST MODEL WITH ENSEMBLE MEMBERS GFS-WRF-ANN

Once the model was trained with the control running GFS-WRF weight coefficient of ANN model are charged in operational forecast model, with 30 ensemble is produced every 6 hours. Forecast are implemented for the full wind power installed capacity of Uruguay with a time horizon of 24 hours. Figure 2 show Operational forecast output of full installed capacity of 1457 *MW* in 37 wind farms, 01/12/2022 24 hours of time horizon.

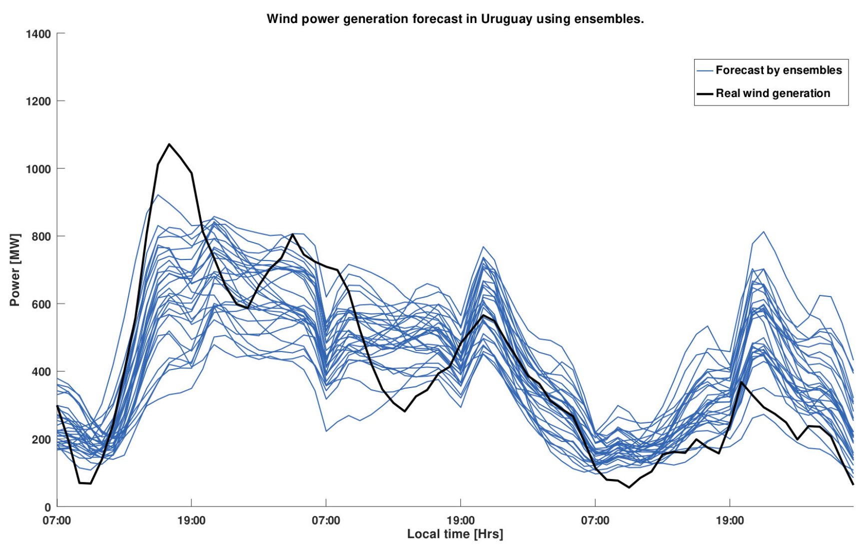

Figure 2. Operational forecast output of full installed capacity of 1457 *MW* in 37 wind farms, 01/12/2022 24 hours of time horizon, blue lines 30 ensemble members, black line real wind power production

5. CONCLUSIONS

It was shown an operational wind power forecast model for 37 wind farms, the methodology implies the train is done with a control running of GFS-WRF once the ANN is trained the operational power forecast model consider as input 30 ensemble members GFSENS-WRF. Further analysis of uncertainty as function of time horizon is need to be done.

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