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LSTM model for wind speed and power generation nowcasting †

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Abstract: In the following work, the design of an LSTM-type neural network model for wind speed and power generation nowcasting, every 10 minutes and up to two hours, is presented. For this, the wind speed measurements were used every 10 minutes at different heights above the ground, coming from the Measurement Tower located in Los Cocos, in the province of Holguín (Cuba), where the wind farms Gibara I and II are located. The real data is complemented with the wind speed numerical hourly forecasts from SisPI. The data covered the period between February 1, 2019 and January 31, 2020, that is, one year of measurement. Several LSTM models were built and evaluated considering only the measurements and combining the measurements with the forecasts generated by SisPI. The results suggest that the constructed models perform better than other more traditional statistical models and than other neural network models used in the country for similar purposes.

Keywords: wind speed and power generation nowcasting; renewable energy sources; artificial neural networks; SisPI

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1. Introduction

Non-conventional energy sources have been reaching a remarkable development and acceptance in recent decades and their use has been very beneficial for the environment, by reducing the use of fossil fuels that assert the greenhouse effect and climate change. Wind energy is one of those unconventional sources and in particular for Cuba it is an alternative in development. According to [1], the country currently plans to install more than 300 MW by the year 2030. A total of 13 wind farms will assume this energy production [2] and already in 2020 the generation of electricity from wind energy assumed the 6% in the Cuban electrical system. Given the intermittency and variability of the wind resource, the National Electroenergetic System must be prepared to assume the generation of electricity from conventional sources at times when it cannot be generated from wind. The way in which this can be guaranteed is by having wind forecasts at the installation sites of the wind farms. These forecasts are very short term, ranging from a few minutes to 2 hours. Research aimed at very short-term forecasting is mainly based on time series or artificial intelligence, or the combination of both in hybrid methods. Can be cited as examples the works by [3,4]. Also exists some results using numerical forecast models, the persistence method, the nearest neighbor method [5] and, wavelet and neural networks [6]. In Cuba, related to predictions for wind purposes, there are the works of [7-10] where short-term forecasts of wind speed were generated with the Weather Research and Forecast (WRF) numerical model, with statistical models and with the use of neural networks. However, only [10] addressed the very short-term prognosis. In addition, in this investigation only real data is used to generate the forecast, and yet there are not a few situations in which it is not possible to obtain the measurement, which would make it impossible to obtain the forecasts in this way. The foregoing leads us to propose this research, where in addition to the use of real data, the forecast of the WRF model is used, so that it can be used alternatively in the event of a measurement failure. The method used is an LSTM type neural network.

2. Methods and Materials

For the generation of very short-term wind forecasts, one year of measurements was taken from Torre Los Cocos, located near the Gibara I and II wind farms. The time period goes from February 1, 2019 and January 31, 2020. In this tower, wind measurements are obtained at 10, 30, 50 and 100 m height every 10 minutes. In this work only the results using the measurements at 50 m height are shown.

In addition, the numerical forecasts were taken on the 3km resolution simulation domain (see Figure 1) offered by the Short-range prediction system (SisPI, by the acronym in Spanish) [11 ,12]. The physical configuration of the WRF used in SisPI can be consulted in [11 ,12]. Since SisPI offers hourly forecasts, it was necessary to make an interpolation to obtain the wind series produced by the WRF every 10 minutes, to make the numerical forecasts compatible with the measurements.

With both data sources, sets of 12 inputs were generated every 10 minutes to forecast 12 outputs also every 10 minutes until reaching the 2-hour forecast.

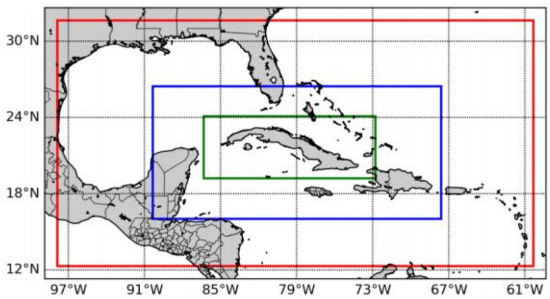


Figure 1. Simulation domains for SisPI. The green square corresponds with 3km resolution domain used in this study.

Several LSTM-type neural network models were used to generate wind force forecasts of up to 2 hours. Figure 2 shows the configuration with best performance used with the data from Torre Los Cocos only, and combining it with the SisPI numerical forecasts.

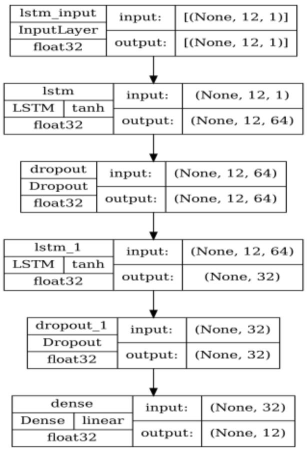


Figure 2. LSTM configuration.

For the evaluation, in addition to the validation set, four study cases (2019/03/11, 2019/05/28, 2019/08/02 and 2019/11/18) corresponding to different months of the year were left out of the training, in which different wind regimes are represented. Root mean absolute error (MAE), root mean square error (RMSE), and Pearson's correlation are used to verify the results.

3. Results and Discussion

Figure 3 shows the mean absolute error obtained when forecasting 12 periods spaced every 10 minutes, for the subset of data taken for the validation of the LSTM model training. The red curve corresponds to the forecast using only real data while the blue curve refers to the combination of the real data with the SisPI forecast. It is noteworthy, in both cases, a growth of the MAE as the forecast moves away from the initial terms. However, it can be seen how, on average, the ability of the LSTM-type network is very high, with a MAE of less than 0.8 m/s, being even less than 0.5 m/s for the first 6 forecast periods. It is striking how the inclusion of the model information offers better results, with the MAE being slightly lower, which is a very good result, considering that in operational practice measurements are often lacking.

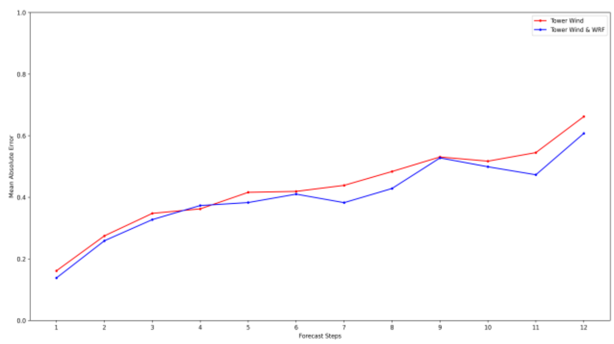


Figure 3. Behavior of the MAE for the 12 forecast terms of the validation set. The red line represents the results with the data from Torre Los Cocos and the blue line corresponds to the results obtained by training the LSTM with the SisPI forecast and the tower observations.

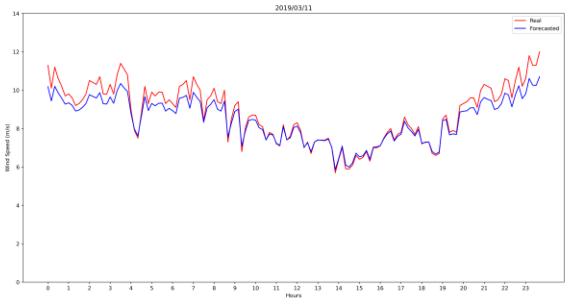
3.1. Verification for the study cases

Taking a look at the results obtained for the selected case studies, Table 1 summarizes the values of the different metrics used. Note how, contrary to the average behavior observed previously, in these cases the forecast generated by the LSTM model that combines SisPI and the observations is worse than when only the wind measurements are taken into account. However, the results are still good and the errors were below 1 m/s except for May 28th, 2019. Future research should delve into the type of meteorological situation for which the SisPI is failing to represent the field of wind. Regarding the correlation, the behavior is similar with both training sets.

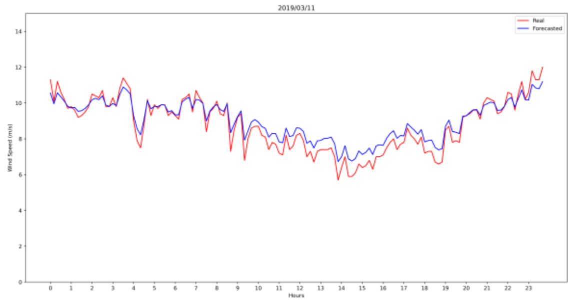
Table 1. Evaluation of the forecast of the LSTM model for the case studies. The left column corresponds to the LSTM model built with real data only and the right column combining SisPI and observations.

Metrics	2019/03/11		2019/05/28		2019/08/02		2019/11/18	
MAE	0.36	0.39	0.50	1.15	0.22	0.60	0.15	0.77
Pearson correlation	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99
RMSE	0.23	0.22	0.36	1.40	0.17	0.47	0.04	0.61

Figure 4 presents the graphs of the predicted wind strength, taking the first period of time of each group of 12, for the study cases. Likewise, the red curve corresponds to the results using the LSTM model trained with observations only and the blue curve, including the SisPI data.



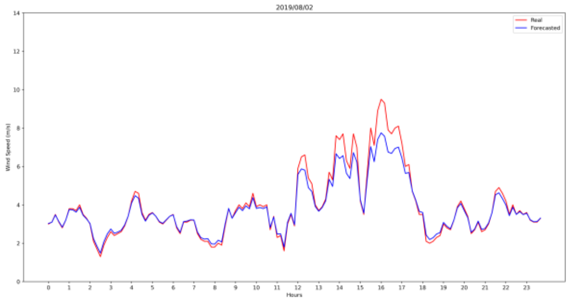
(a)

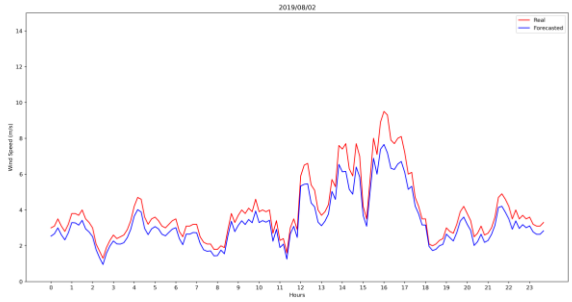


(b)

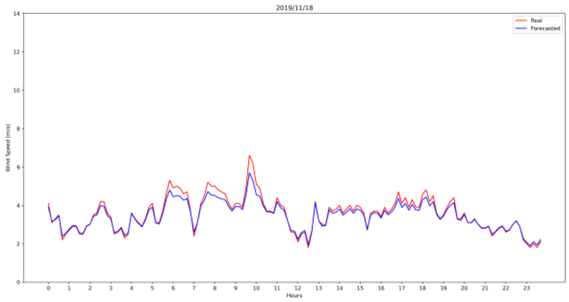
(c)

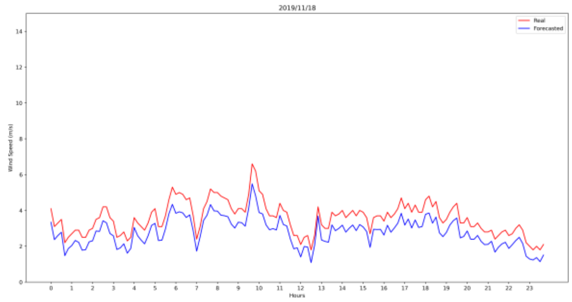
(d)





(e) (f)





(g) (h)

Figure 4. Forecast wind values for each of the case studies (rows in order 2019/03/11, 2019/05/28, 2019/08/02 and 2019/11/18) using the LSTM model trained with observations only (left column) and the LSTM model input with SisPI and observations (right column).

The rows show the results for the cases following the order 2019/03/11, 2019/05/28, 2019/08/02 and 2019/11/18, while the columns show for each case the forecast obtained with the observations alone (Figure 4 a,c,e,g) and with the combination of SisPI and measurements (Figure 4 b,d,f,h). In this case, the red lines represent the measured behavior of the wind, while the blue curve represents the forecast. It is easy to see that with the SisPI forecast, the error is larger, however the good news is that it seems to be a systematic error which can be treated with a bias correction method.

4. Conclusions

After the results presented, we can arrive at the following conclusions:

- The LSTM model elaborated both with data from the Los Cocos tower and with the combination of the same with the SisPI forecasts presents a very good ability to forecast the force of the wind.
- The forecasts including the SisPI data have a slightly higher MAE and RMSE, however correction is possible as they are systematic errors.
- In the absence of observations, it is possible to use the SisPI data as an alternative for very short-term forecasting.

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Conflicts of Interest: The authors declare no conflict of interest.

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