Wind-Speed Modelling Using Fourier Analysis and Nonlinear Autoregressive Neural Network (NAR)

RUEDA-BAYONA, J.G. a*, CABELLO J.J.b, SCHNEIDER, I.L. c

a Universidad Militar Nueva Granada. Engineering Faculty. Civil Engineering Program, Bogotá, Colombia.

b Universidad de la Costa. Energy Department, Barranquilla. Colombia.

c Universidad de la Costa. Civil and Environmental Department, Barranquilla. Colombia.

*Corresponding author, juan.rueda@unimilitar.edu.co, ruedabayona@gmail.com.

Abstract
This paper presents a methodology for analyzing and predicting local wind-speed with high time resolution (hourly) and long-term (years) horizon, through Fourier analysis and Nonlinear autoregressive network (NAR). Engineering activities and wind energy applications (wind power estimation and power system operations) requires accurate wind-speed modelling. Additionally, wind time series exhibits nonlinearities, gaps and scarce of in situ data, therefore, the proposed methodology is able to deal with those requirements. Considering the lack of in situ data, the research recommends a data assimilation and natural variability identification before atmospheric variable forecasting. The study used a wind-speed time series from the North American Regional Reanalysis (NARR) project database (1980 to 2014) and compared against in situ data for assimilation. Then, Fourier identified natural variability for wind-speed at local stations. Also, we found a quarterly variability associated with Madden Julian fluctuations, semiannual, annual, and 6-year variability (ENSO). NAR model predicted successfully the wind-speed with 3 hours’ interval for 11 years according to 0.90 of correlation. The low computational cost and the accuracy of modelled results obtained in this research, allow to implement the proposed methodology for diverse engineering and scientific research applications.

Keywords: wind-speed, Fourier, NAR, reanalysis, wind potential, modelling.

1. Introduction
Understanding the hydrological and climatological behavior is crucial for engineering purposes and social needs. Every civil engineering project for water resources management (dams, rivers, buildings, roadways) requires hydrological studies. Agriculture depends on climate variability for planting crops, and renewable energy industries demand wind-speed potential for sustainable energy extraction; these activities require a climate variability understanding for specific places. In planning and designing civil infrastructure (wind farms), wind-speed modelling is required for establishing impacts derived from risk and menace for different environmental situations. Similarly, some engineering tasks need time series data with interval resolution about one hour. Fulfilling these needs are limited by data availability, especially if the study site does not have nearby climatological stations, or data sets do not have adequate time resolution for statistical and probability analysis. Wind-speed forecasting horizon can be classified in very short-term (a few seconds to 30 min ahead), short-term (30 min to 6 h ahead), medium-term (6 h to 1 day ahead), and long-term (more than 1 day) [1]. Wang et al. [2] classified wind forecasting
according prediction horizon and applied methodology. The prediction horizon established three categories: immediate-short-term forecasting (hours ahead), short-term forecasting (day ahead) and long-term forecasting (multiple days ahead). Respect to applied methodology, the forecasting was classified as physical (deterministic), statistical (historical data required), and hybrid.

Amjady et al. [3] applied a ridgelet neural network (RNN) to predict wind for several days, and used 1176 hourly wind data samples for training, and 24 samples for validation. They proposed a prediction strategy for wind forecasting through differential evolution algorithm with a novel crossover operator. Blonbou [4] interested in wind-speed short-term forecasting, applied an Elman neural network. The author used 600 samples with 30 minutes of time interval, and 800 samples for validation.

Carvalho et al. [5] coupled three wind models with mesoscale and microscale spatial resolution to evaluate wind resource in two sites; they provided three methodologies to estimate wind potential through numerical modelling and in situ data assimilation. The research indicates that mesoscale output should not be used directly in wind farm sitting projects. As a result, the study recommends applying with extreme caution mesoscales and microscale coupling in areas with complex topography. They conclude that wind mesoscale-microscale models for wind assessment cannot still be seen as a substitute to locally acquired wind data for specific wind farm projects. The research of Wang et al. [6], configured a hybrid forecasting scheme to wind-speed forecasting through three methods: Extreme Learning Machine (ELM), Ljung-Box Q-test (LBQ) and Auto-Regressive Integrated Moving Average (SARIMA). They compared the proposed scheme against other models (ARIMA, SARIMA, Back-Propagation neural network and ELM), and indicate that their scheme exhibited stronger forecasting ability for daily and monthly wind-speed.

A combined forecasting models for wind energy forecasting were applied by Xiao el al. [7]. The research reviewed combined models to predict wind and classified wind-speed forecasting approaches. They applied the no negative constraint theory (NNCT) combination model, the artificial intelligence algorithm combination model, and modelled wind-speed with hourly interval with short-term horizon (250 hours ahead).

Carpinone et al. [8] adapted discrete time Markov chain models to forecast wind power, considering real wind power time series data. The authors modelled wind power for a very short-term horizon (2 hours) with 10 minutes of time steps. They concluded that their method allows to directly estimate the wind power distributions without requiring restrictive assumptions on wind power probability distribution. Liu et al. [9] applied a secondary decomposition algorithm to reduce the non-linearity in wind-speed time series. They used a secondary decomposition algorithm to reduce the nonlinearity of inputs and wavelet decomposition for natural modes identification. In consequence, the research concluded that modelled results improved after reducing nonlinear noise of training-data.

Recently the learning or artificial intelligence techniques, hybrid modelling, and autoregressive method, are being tested and strongly recommended for short-term forecasting [10], [11], [12], [13].

In 2016, Shrivastava et al. [14] set a multi-objective differential evolution (MODE) algorithm for generation of prediction intervals (PIs) to capture the uncertainty related to forecasts. Additionally, they used a Support Vector Machine (SVM) to generate Pareto-optimal solutions. The researchers modelled wind-speed with 1-hour time interval and 180 hours of forecasting horizon; their conclusions indicated that proposed methodology can be further improved through a feature selection technique for determining more relevant input features, and proposed methodology can also be extended to longer look-ahead forecast.

To forecast wind power time series with ultra-short term horizon, Zhao et al. [15] configured a bidirectional mechanism and backward ELM network. They modelled in six time horizons (1-6 hours), and did a comprehensive error analysis to compare the model performance with other approaches. Their conclusions indicated that individual backward model is effective and feasible for wind power forecasting, and further research is needed to improve its stability and accuracy. Wang et al. [16] did a review of wind-speed forecasting, applications, time horizons and methods. The research presented 8 strategies for realizing multi-step wind-speed forecasting (4-day horizon) with machine learning methods and compared 48 different hybrid models based on the 8 strategies. Main conclusions showed that Lazy Learning is a robust method for predicting wind-speed, also, EEMD method showed superior results regardless of the measure used for the
Comparison. Additionally, ALL-DDVC performed better than other combination models, and can be directly applied to missing or abnormal time series.

A nonlinear autoregressive (exogenous) model for one-day-ahead mean hourly wind-speed forecasting was applied by Zhao et al. [17]. The research used ARIMA technique and Fibonacci search method to select the best lag structure and bandwidth. Authors applied the NAR model in four real-world case studies in China and, concluded that the method had a good one-day-ahead wind-speed forecast performance owing to the help of iterative correction operation, and the introduction of NWP exogenous information can further improve accuracy. In order to predict wind-speed data, Zhang et al. [18] configured two hybrid model which combine empirical mode decomposition (EMD), feature selection with artificial neural network (ANN) and support vector machine (SVM). They modelled 744 hours of wind-speed with hourly interval and, concluded that the combination of EMD with ANN or SVM can improve the performance for short-term forecasting.

Wang et al. [19] used an improved empirical mode decomposition (EMD) and GA-BP neural network for ultra-short term (10 min) and short term (1 h) wind-speed forecasting. They compared the modelled results against a wavelet neural network to illustrate the effectiveness of the proposed method and, concluded that proposed hybrid model is much better.

Zhao et al. [20] built a hybrid scheme for wind-speed multi-step forecasting for 4 days’ operational wind forecast. The hybrid scheme comprises of coupling a physical weather model named WRF¹, to a novel Fuzzy System and Cuckoo search algorithm. The authors settled two main conclusions. First, the higher horizontal resolution does not always guarantee high accuracy, and second, the hybrid scheme improved the numerical results in the 96 virtual points for a short-term horizon.

The research of Lydia et al. [21] predicted superficial wind-speed (10 m) up to 1 h by means of a linear and a nonlinear autoregressive moving average model (ARMAX). Researchers analyzed wind direction and annual trends from in situ data, and settled forecasting for wind-speed with 10-min ahead. They recommended an appropriate exogenous variable selection, and the use of metaheuristic techniques for better results. The authors remark that heuristics methods are a research area to be explore.

In 2017 Feng et al. [22], developed a data-driven multi-model wind forecasting methodology based on two-layer ensemble machine learning technique, for 1-hour-ahead wind-speed forecasting. They suggested as potential future work, to validate the effectiveness of the developed multi-model framework with different time horizons in short-term forecasting; temperature and humidity can also be forecasted by the proposed method.

Liu et al. [23] applied a neuro-fuzzy inference system (ANFIS) to apply a back propagation neural network (BPNN), radial basis function neural network (RBFNN), and least squares support vector machine (LSSVM). The authors modelled wind power for short-term horizon (48 hours), and required a preprocessing method based on Pearson correlation coefficient to enhance mapping accuracy of the modelling results. They remarked that their results did not represent the models’ actual performance in a real case scenario where forecasted meteorological data instead of measured meteorological data will be used as input. As future work authors suggest to obtain numerical weather prediction data and refine it with advanced data preprocessing method in order to reduce its error and associated impact on wind power forecasting models’ performance.

Several research about wind forecasting with short-term horizon through linear fuzzy neural network [24], multivariate autoregressive moving average model [25], wavelet transform with convolutional neural network [26] was recently published.

A modelled wind-speed time series (600 h ahead) considered as short-term forecasting horizon was created by Akçay and Filik [27]. They estimated the auto-correlation functions from ensemble averages, then, applied a one-step-ahead and multi-step-ahead Kalman filter predictors for wind forecasting. Authors remarks that foremost advantage of the proposed scheme over most hybrid techniques is the absence of iterative search procedures in the parameter space, which are not guaranteed to converge to optimal values unless suitably started. According to cited literature, we identified that local wind-speed forecasting does not have a long-term horizon (several years) with high interval resolution (hourly), and the input training-data comes from in situ time series shorter than 30 years. Most of neural networks and statistical methods used by the cited authors required a previous filtering or signal decomposition in order

to reduce the nonlinearities of input training-data. Taking into account the earlier considerations and limitations observed in cited literature, such as data availability, filtering raw data, and forecasting horizon, we considered necessary to contribute to these challenges. This research presents a novel methodology integrated by three steps: 1- Data assimilation, 2- Identification of natural variability and 3- variable forecasting. The first step of the proposed method suggests assimilating long-term wind-speed information from North American Regional Reanalysis (NARR) [28] for a specific place. The second step applies the Fourier analysis to determine trends and climate variability of the wind-speed, and to generate the input data for the nonlinear autoregressive neural network (NAR) model. The third step takes the modelled data by Fourier and forecast the atmospheric variable (wind-speed) through the NAR model.

2. Methodology.

2.1. Fourier analysis

Depiction and prediction of local wind-speed may be performed through a harmonic analysis, which consist in decomposition of time series in harmonics or regular waves, with defined period and phase. This harmonic decomposition aims to identify natural oscillations of climatological parameters, which could explain the natural climatique variability. We can represent the original time series through the sum of all constituent harmonic waves from Fourier coefficients as:

\[ y(t_n) = \frac{a_0}{2} + \sum_{k=1}^{M} a_k \cos(\omega_k t_n) + b_k \sin(\omega_k t_n) \]  

\( k \) is the harmonic, \( \omega_n \) is the angular frequency of \( k \)-th harmonic in radians, and \( M \) is the number of harmonics to be found. As a result, \( t_n = n \Delta t \) and \( \omega_n = 2\pi \frac{k}{N} = 2\pi f_k \). Where \( \Delta t \) is the time interval of records and \( N \) is the number of observations from the time-series. The minimum frequency is determined from measurement records as:

\[ \omega_1 = \frac{1}{\Delta t} \rightarrow \omega_1 = \frac{2\pi}{\Delta t} \]  

\( k = 1 \rightarrow f_0 = \frac{1}{N} \rightarrow \omega_1 = \frac{2\pi}{N} \)  

The maximum frequency is determined considering that \( \omega_0 \leq \omega \leq \omega_N \). Eq. (3).

\[ k = M \rightarrow f_M = \frac{1}{2\Delta t} \rightarrow \omega_1 = \frac{\pi}{\Delta t}, M = \frac{N}{2} \]  

Fourier coefficients now are determined using Eq. (4, 5, 6 & 7):

\[ a_0 = \frac{1}{N} \sum_{n=1}^{N} y(t_n) \]  

\[ a_k = \frac{1}{N} \sum_{n=1}^{N} y(t_n) \cos(\omega_k t_n) \]  

\[ a_{N/2} = \frac{1}{N} \sum_{n=1}^{N} y(t_n) \cos(\pi \cdot t_n) \]  

\[ b_k = \frac{1}{N} \sum_{n=1}^{N} y(t_n) \sin(\omega_k t_n) \]  

Then, we simulate the signal through Eq. (8).

\[ y(t_n) = \frac{c_0}{2} + \sum_{k=1}^{M} C_k \cos(\omega_k t_n - \theta_k) \]  

Amplitude of every single harmonic is calculated by Eq. (9).

\[ c_k^2 = a_k^2 + b_k^2 \]  

Finally, Eq. (10) allow calculating phase of each harmonic:

\[ \theta_k = \tan^{-1} \frac{b_k}{a_k} \]
are applying a continuous wavelet transform [40], or a discrete wavelet transform with Haar basis functions [41].

2.2. Nonlinear autoregressive network (NAR).

An artificial neural network (ANN) is a structure integrated by interconnected units known as artificial neurons. Every neuron has an input/output associated to a local computation or mathematics function [42]. The ANN is a distributed computational scheme, structured by elemental units with low processing capacity, links between neurons, and variable parameters (weights, learning rate, and bias) which improve the network performance. The advantage of ANNs is their ability to be implemented as an arbitrary function approximation mechanism, which it learns from observed information [43], therefore, input data characteristics defines the suitable model and learning algorithms. ANNs are used on quantum-chemistry applications [44], numerical modelling for oceanography [45], system identification and control [46], estimation of electricity price for energy market [47], even human face image identification for age classification [48]. The Backpropagation neural network (BNN) is the most used type network, equivalent to a multivariate multiple nonlinear regressions model [49], where BNN trains the network until inputs are similar to expected outputs. BNN presents limitations in gradient descent algorithm, where is possible that global minimum of error function could not be found. The previous issue is caused by non-convexity of error functions in neural ANN; however, Yann L et al. [50] argue that this problem is not present in many ANN applications. The NAR model has a similar structure of a BNN, where the elements that integrates the net are: inputs from a time series \( y(t) \), weights \( w \), bias \( b \), hidden layers \( k \), and the outputs \( y(t) \) [51]. NAR is different to BNN due to the model takes the output time series as inputs, doing a dynamic feedback to the neurons and letting to each perceptron increase the learning rate. For the model, it is possible to consider a time delay (td); this time delay gives the number of past predictions that helps feeding the model, allowing the autocorrelation and covariance improvement Eq. (11), where \( h \) is forecasting horizon:

\[
y(t + h) = f(y(t - 1), ..., y(t - td)) \tag{11}
\]

This research configured a NAR model with one hidden layer, which activates weights through sigmoid function; output layer applies a linear function for validation (Fig. 1).

**Fig. 1.** NAR model structure.

First the NAR model takes the input data that will guide to the weights to evolve considering the output results. The weights actualizations according to the backpropagation method consist in consecutive steps forward and backwards. The step forward builds the \( \text{net}_t \) through the summation of j-th product between inputs and weights (12):

\[
\text{net}_t = \sum w_{kj} y_j \tag{12}
\]

The NAR network verifies the temporary result by sigmoid function; if temporary result \( z_j \) is positive (13) the result is selected:

\[
z_j = \frac{1}{1 + e^{-\text{net}_t}} \tag{13}
\]

Before the finalization of forward step, the procedure determines a total temporary \( \text{net}_t \) (14) in order to estimate the error (15):

\[
z_t = \sum w_{kj} z_j \tag{14}
\]

\[
\text{error}_t = 1 - z_t \tag{15}
\]
If the error is below a given threshold, the forward step completes. Now the backward propagation starts through the estimation of gradients of output and hidden layer (16), (17):

\[ \delta_j = \text{error}_j \cdot z_j(1-z_j) \]  
\[ \delta_i = \sum \delta_j w_{kj} \cdot z_j(1-z_j) \]  

After propagation of error, Delta rule updates the weights (18):

\[ \Delta w_{kj} = \eta \cdot \delta_i \cdot z_i \]  

Delta rule is the final step backwards and will stop the NAR calculations until user considers that updated weights simulate properly the input training-data. Finally, the NAR model sets the final number of layers, weights and biases, which are able to predict the time series.

3. Results and analysis

The proposed method begins with the assimilation and adjustment of Reanalysis data through linear regression analysis. After data-management, method identifies natural variance and oscillations modes through Fourier analysis, and generate input data for the NAR model. Finally, the third step through the NAR model forecasts the wind-speed with 3-hourly time-interval (Fig. 2).

![Fig. 2. Main steps of the proposed methodology.](image)

The Fourier model through trigonometric functions allows to identify oscillations of the time series, what represent the climate variability of atmospheric variable in the study area. The Fourier model fails to model the real variability of the wind-speed due to the high non-linearity of the variable, however, represent the overall behavior of the atmospheric variable, what is very important for the NAR model. The NAR model takes inputs data and delivers outputs, then, the Fourier inputs and the NAR outputs are taken again by the NAR model to update the weights. The NAR model learn the overall behavior from previous raw data and from Fourier modelled data, and learn to reproduce the non-linearities identified from the previous raw data. Finally, the NAR model is ready to forecast the wind-speed considering climate variability given by Fourier model, and non-linear effects given by the initial raw data.

3.1 Data assimilation.

The first step of proposed methodology, begins with the selection of a climatological stations located at Cartagena city (Fig. 3). The climatological station belong to Instituto de Hidrología, Meteorología y Estudios Ambientales de Colombia (IDEAM) [52]. The wind-speed data belong to NARR database [28], which begins from January 1-st of 1979 up to date. NARR has 0.3 degrees of spatial resolution (32 km), with time interval of three hours. The study applied a linear regression to assimilate the reanalysis data; it was extracted the NARR data for 2013 and 2014 years, due to the climatological station have hourly wind data between these two years.

![Fig. 3. Location of the in situ climatological station (10.442997 N 75.510799 W).](image)
The statistical results of linear regression for wind-speed (Fig. 4), showed a correlation coefficient of 0.85, a p-value < 0.05, with a slope of 0.6 and no interception. The statistical result shows that reanalysis data compared against in situ data have high, direct and positive correlation between them.

Fig. 4. Assimilation of the reanalysis data (NARR) using wind speed data of the climatological station (IDEAM) located in Cartagena city.

3.2 Identification of natural variability.

To identify the natural oscillations of wind speed time series associated to the local climate variability of Cartagena city, a periodogram was generated using Fourier analysis. The periodogram showed through the peaks of amplitude the natural periods of wind-speed. These peaks (Fig. 5) evidenced the climate variability events such as the sea-breeze (1 day), seasonal (5.5 months) and annual variability (10.9 months), possibly the El Niño effect (5.39 years) and the Pacific Decadal Oscillation (11.08 years).

Fig. 5. Periodograms generated through the Fourier analysis for the wind-speed time series of Cartagena climatological station.

In order to generate the input data for the NAR model, the Fourier model simulated 1.71 years (5000 three-hourly records) of wind-speed for the Cartagena climatological station. As a result, it is showed that Fourier represent well the oscillation and trend but fails in accuracy in some hourly intervals. Accordingly, the linear regression between the in-situ (Raw data) and modelled (Fourier) showed a correlation coefficient of 0.22. However, the modelled data by Fourier will be use as input data for the NAR model; the NAR model through its weights and filter functions will adjust the input data to generate a calibrated output data.
3.3 Variable forecasting

After analyzing the natural variability of wind-speed at Cartagena station, the final step was the implementation of a NAR model. Accordingly, this study created the NAR network through a MATLAB code, and configured a design of experiments to analyze the model performance. After changing number of neurons, hidden layers and time delays, the results indicated that best performance of a NAR network required one hidden layer with three delays. The NAR model takes the input data from the Fourier model and forecast the wind-speed considering the non-linearities of the wind behavior. As a result, the NAR model took 11 years of the wind speed-time series with three-hourly time interval for training, calibration and forecasting. First, NAR model used the first 25% of data for training (7500 records) and used 17500 records for validation. Then, the NAR model took the input data generated by Fourier and forecasted the last 5000 records (dash-line rectangle) of wind-speed (Fig. 7).

Fig. 6. Wind-speed modelling of Cartagena station using Fourier model for 1.5 years (15,000 hours) with three-hourly interval; starting from 00:00 hr of April 18th 1988 to 00:00 hr of February 27th 1990.
Fig. 7. Wind-speed modelling of Cartagena station for 11 years for (90,000 hours, 30,000 records), starting from 01:00 hr of January 1st 1979 to 02:00 hr of February 27th 1990. The dash-line rectangle represents the time period of input data generated through the Fourier model (Fig. 6).

As seen in Fig. 7 the NAR model forecasted the wind-speed for 1.71 years with three-hourly time interval (dash-line rectangle). Then, it is observed that the input data modelled by Fourier guided to NAR model, and allowed to the neural network to forecast with precision. To verify the quality of the forecasting, it was compared the model and the wind-speed raw data through linear regression. The results indicated a high precision of the NAR model, due to the r coefficient of 0.9, what evidenced that NAR model forecasted with success the wind-speed data. The Table 1 indicates the structure of the calibrated NAR model for the Cartagena station.
Fig. 8. Scatter plot of Wind-speed modelling of Cartagena station for 11 years for (90,000 hours), starting from 01:00 hr of January 1st 1979 to 02:00 hr of February 27th 1990. Raw data represents the target data for the NAR model.

Table 1. RNA parameters and statistical results of validation for the Cartagena station.

<table>
<thead>
<tr>
<th>Station</th>
<th>Cartagena</th>
</tr>
</thead>
<tbody>
<tr>
<td>Time delay</td>
<td>1, 7, 13, 19</td>
</tr>
<tr>
<td>Input weight</td>
<td>0.7755, 0.3188, 0.0136, -0.1035</td>
</tr>
<tr>
<td>Layer weight</td>
<td>1.0217</td>
</tr>
<tr>
<td>Bias</td>
<td>0.1332, -0.1451</td>
</tr>
<tr>
<td>r coefficient</td>
<td>0.8915</td>
</tr>
<tr>
<td>p-value</td>
<td>0</td>
</tr>
</tbody>
</table>

The proposed NAR model evidences a simple structure (Table 1) able to be implemented in different study areas of scarce in situ data. The NAR model used 25% of data for training, 58% of data for validation, and 17% for forecasting. The 0.9 of correlation (Fig. 8) and low computational time (less than 10 minutes) evidenced efficacy and efficiency of the NAR model. According to the results showed above this research presented the capacity of Fourier to identify the local climate variability and to model the behavior of wind-speed. Also, it...
was evidenced the forecasting precision of the NAR model (Fig. 7, Fig. 8, and Table 1) to model with high resolution-interval and long-term horizon. Due to the forecasting horizon in the literature review did not exceed one year of modelling, then, this research suggests using the proposed methodology.

The proposed method in this paper integrates three main procedures: assimilation, identification, and forecasting. First, the method started with the assimilation and adjustment of Reanalysis data through linear regression analysis. After, the second step method identified natural variance and oscillations modes through Fourier analysis, and generated the required input data for the NAR model. The last step forecasted the wind-speed with 3-hourly time-interval for 1.71 year through the NAR model. According to the results, the implemented NAR model simulated with high precision (0.9 of correlation) 11 years of wind-speed data and forecasted 1.71 years with 3-hourly time-interval. It was identified the natural oscillations of climate variability, using the Fourier model; the five peaks observed in the periodogram showed the local variability, such as sea breezes, seasonal and inter-annual events (El Niño, Pacific Decanal Oscillation). Gathering the results Fourier analysis and NAR, this research observed that these two techniques extract principal components, from dimensionality reduction of data sets. The two methods differ in the mathematics solution; the Fourier analysis determines harmonics from trigonometric functions and neural networks combine probabilistic methods and filter functions for selecting weights that guide to target solution. The proposed methodology allows user to identify climate variability...
through Fourier analysis, and recommends a NAR model to forecast atmospheric variables with long-term horizon and short-time interval; the method can be used for deterministic approaching in engineering and research applications during scarce in situ data. Finally, this paper deals wind-speed nonlinearities and scarce in situ data of time series, to improve long-term and high-resolution forecasting for engineering and wind energy applications.

5. Acknowledgements.
The authors thanks to Universidad del Norte for the financial support through UNINORTE doctoral Fellowship (2013-2017) [grant numbers UN-OJ-2013-22022, UN-OJ-2013-22058], and the Department of Civil Engineering for the academic and administrative support.

6. References.


