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Article

Prediction of Wind Speed Using Hybrid Techniques. Three locations: Colombia, Ecuador and Spain.

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Abstract: This paper presents a methodology to calculate day-ahead wind speed predictions based on historical measurements done by weather stations. The methodology was tested for three locations: Colombia, Ecuador, and Spain. The data is input into the process in two ways: 1) as a single time series containing all measurements, and 2) as twenty-four separate parallel sequences, corresponding to the values of wind speed at each of the 24 hours in the day over several months. The methodology relies on the use of three non-parametric techniques: Least-Squares Support Vector Machines , Empirical Mode Decomposition , and the Wavelet Transform . Also, the traditional and simple Auto-Regressive model is applied. The combination of the aforementioned techniques results in nine methods for performing wind prediction. Experiments using a MATLAB implementation showed that the Least-squares Support Vector Machine using data as a single time series outperformed the other combinations, obtaining the least mean square error .

Keywords: Empirical Mode Decomposition; Hybrid techniques; LSSVM; Wavelet transform; Wind speed prediction

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1. Introduction

At the end of the XX century, a change in the trends of energy production began, promoted by concerns about pollution, climate change and the dependence of some countries on the importation of hydrocarbons. In this context, great interest is concentrated in the opportunities offered by renewable technologies as a source of supply in non-interconnected areas and as part of the integrated generation system that participates in the pool in the wholesale market [1,2].

Energy policies in many countries encourage the implementation, expansion and interconnection of alternative renewable energy sources such as photovoltaics, solar thermal, wind, geothermal, hydroelectric, wave, tidal and biofuel. An analysis of these technologies establishes wind energy as the most economical on a large scale [3**?**]. It is remarkable that at the end of 2019 only few countries had more than 20,000 MW of installed capacity of wind energy: China (236,402 MW), USA. (105,466 MW), Germany (61,357 MW), India (37,506 MW), Spain (25,808 MW) and the United Kingdom (23,515 MW) [**?**]. Currently, wind energy production is the fastest-growing energy generation technology, with a connected capacity in the world of 568,409 MW in 2019.

In Latin America [4], Brazil is the leader with 16,643 MW, followed by Chile with 2,150 MW, Uruguay (1,647 MW), Argentina (1,604 MW), Costa Rica (459 MW), Nicaragua (635 MW), Honduras (274 MW) and Peru (375 MW). In Colombia, the advances associated with wind power generation are currently 0.10% of the national capacity, represented by the Jepirachi Wind Farm [5,6] which is regulated by UPME (Colombian Energy and Mining Planning Unit [7]). Since 2014, the Law 1715 [8] offers tax incentives that aims to boost the use of renewable energy sources in the Colombian electricity market (for capacities greater than 20 MW [9]) and in non-interconnected areas.

The entry of wind power into an electrical system brings with it the challenge of including non-dispatchable energy [10]. The difficulty lies in the stochastic characteristics of the wind and

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regardless of certainty that can be had when predicting its future values [11,12]. Prediction errors turn into technical and economic repercussions both for the market operator (due to the reprogramming involved) and for the owners of the generating parks. Modern wind turbines are in the capacity to turn to look for the direction of wind speed. This allows for the greatest possible power generation. Therefore, the prediction focuses on wind speed and not on its direction. [13,14]. However, the aforementioned does not reduce the complexity of the problem due to the characteristics of the wind and the influence exerted by factors such as latitude, altitude, relief, pressure, and temperature.

This paper presents a methodology for the prediction of wind speed in the short term (day-ahead market). The historical data is processing in series (time series) or parallel (prediction hours) using three non-parametric statistical regression techniques:

- Least-squares support vector machine (LSSVM)
- Empirical Mode Decomposition (EMD)
- Wavelet transform (WT)

The application of the methodology is illustrated using a software tool processed in MATLAB® platform in the following cases: 1) Colombia: using historical wind data at the Puerto Bolívar weather station obtained from the Institute of Hydrology, Meteorology and Environmental Studies (IDEAM), 2) Ecuador: wind measurements recorded in the wind farm of San Cristóbal- Galápagos Island obtained by the park's developer, EOLICSA and 3) Spain: Wind data from Puerto de Santa María station in Cádiz. Figure 1 shows the locations studied.

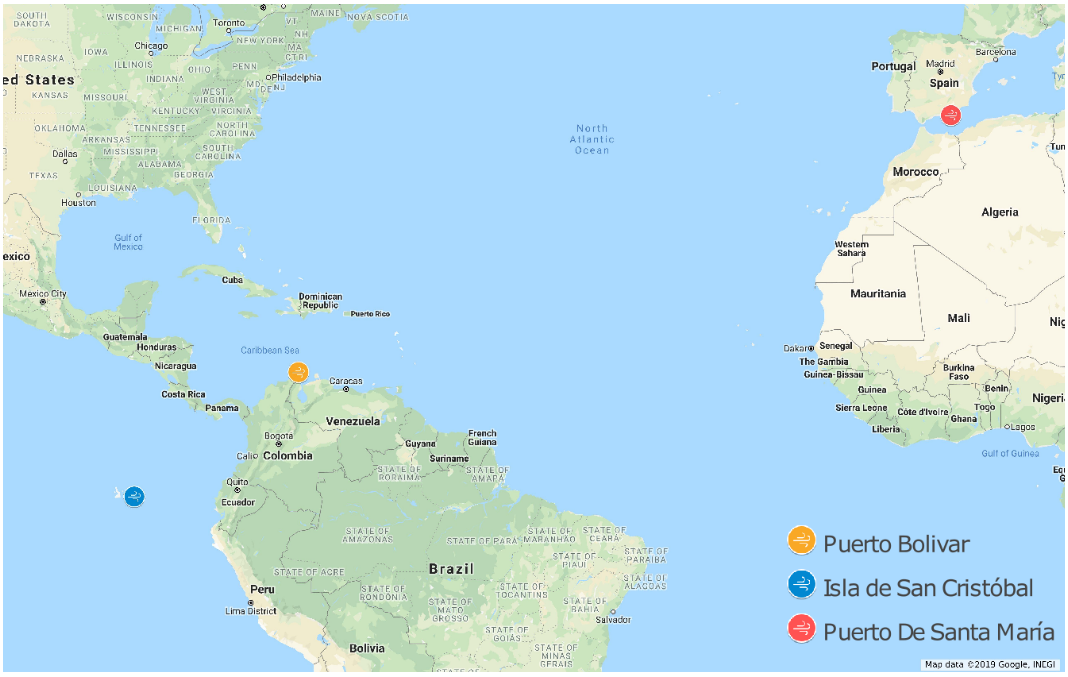

Figure 1. Wind data measurements locations.

2. Materials and methods: wind speed prediction

This section presents a classification of the predictions based on the predicted time horizon. Besides, a description of the applied methodology is made. The prediction methods implemented in the platform are defined and description is made of the non-parametric techniques that are used: Wavelet Transform (WT), Empirical Mode Decomposition (EMD) and Least-Square support vector machine (LSSVM). According to [15] the predictions with time horizon are classified into 4 categories:

Predictions in the ultra short term: for ranges from a few minutes to an hour in advance and its application focuses on adjustment markets, regulatory markets.

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Short-term predictions: from one to several hours in advance. This type of prediction is appropriate to establish the availability proposals in the market of the previous day, which is carried out in the pool or the energy exchange.

Medium-term predictions: from several hours to a week in advance. It allows generation programming to be carried out, this programming must be adjusted with the information obtained with the short-term prediction minimizing the probabilities of deviations in the generation.

Long-term predictions: from one week to one year in advance. It is widely used in the planning of new wind projects, maintenance hours, system expansion, among others.

This methodology is developed to make a short-term prediction (day-ahead market) using statistical methods of non-parametric smoothing or regression. Different authors have worked and proved that decomposing the wind speed in time series partially removes their stochastic volatility. Historical wind speed data follow the composition of a stochastic plus a noisy signal [16–18].

Wind predictions are performed with each of the statistical techniques and make mixtures among them (hybrid techniques). The selected technique will be the one with the lowest mean square error. Individual and hybrid statistical techniques take data in two ways: 1) Series: wind data in each hour of previous days, generating a single vector of data, and 2) Parallel: Wind data in every 24 hours during previous days, generating 24 data vectors. Then decomposition, filtering, and reconstruction techniques are combined as follows:

- Method I (series prediction): Least square support vector machine (SER-LSSVM).
- Method II (series prediction): Decomposition with Wavelet Transform (WT), elimination of high variability component, signal reconstruction (REC) and then use of LSSVM (SER-WT-REC-LSSVM).
- Method III (series prediction): Empirical Mode Decomposition (EMD), elimination of high variability component, signal reconstruction and then use of LSSVM (SER-EMD-REC-LSSVM).
- Method IV (series prediction): Decomposition with Wavelet Transform (WT), elimination of high variability component, use of LSSVM machine to estimate each WT component and then signal reconstruction. (SER-WT-LSSVM-REC).
- Method V (series prediction): Empirical Mode Decomposition (EMD), elimination of high variability component, use of LSSVM to estimate each EMD component and then signal reconstruction (SER-EMD-LSSVM-REC).
- Method VI (parallel prediction): Autoregressive model that estimates the wind in one hour using the simple average of the wind at that same time for previous days (PAR-AVE).
- Method VII (parallel prediction): LSSVM at hourly winds for several days (PAR-LSSVM).
- Method VIII (parallel prediction): Decomposition with WT Wavelet Transform at hourly winds for several days, elimination of the high variability component and then signal reconstruction. Subsequently, LSSVM is used to estimate winds in each of the 24 hours (PAR-WT-REC-LSSVM).
- Method IX (parallel prediction): EMD Empirical Mode Decomposition at hourly winds for several days, elimination of the high variability component and then signal reconstruction. Subsequently, LSSVM is used to estimate winds in each of the 24 hours (PAR-EMD-REC-LSSVM).

The methods will be analyzed considering the filtering and elimination of the components in the decomposition. As a result, the information of the wind speed trend is preserved and the component with the greatest variation is neglected. The reconstructed term refers to the elimination of the residues of the Wavelet transform or the empirical decomposition, to then make the prediction using LSSVM. The purpose of eliminating residues is to have a smoothed signal so that the nonlinear regression of the vector machine fits in a better way to the input data of the model. Figure 2 shows a flowchart for the framework implemented in MATLAB®.

2.1. Wavelet transform

The Wavelet Transform (WT) offers a solution to the problem of the temporal resolution balance compared to the frequency resolution, as presented in other more classical transforms such as Fourier

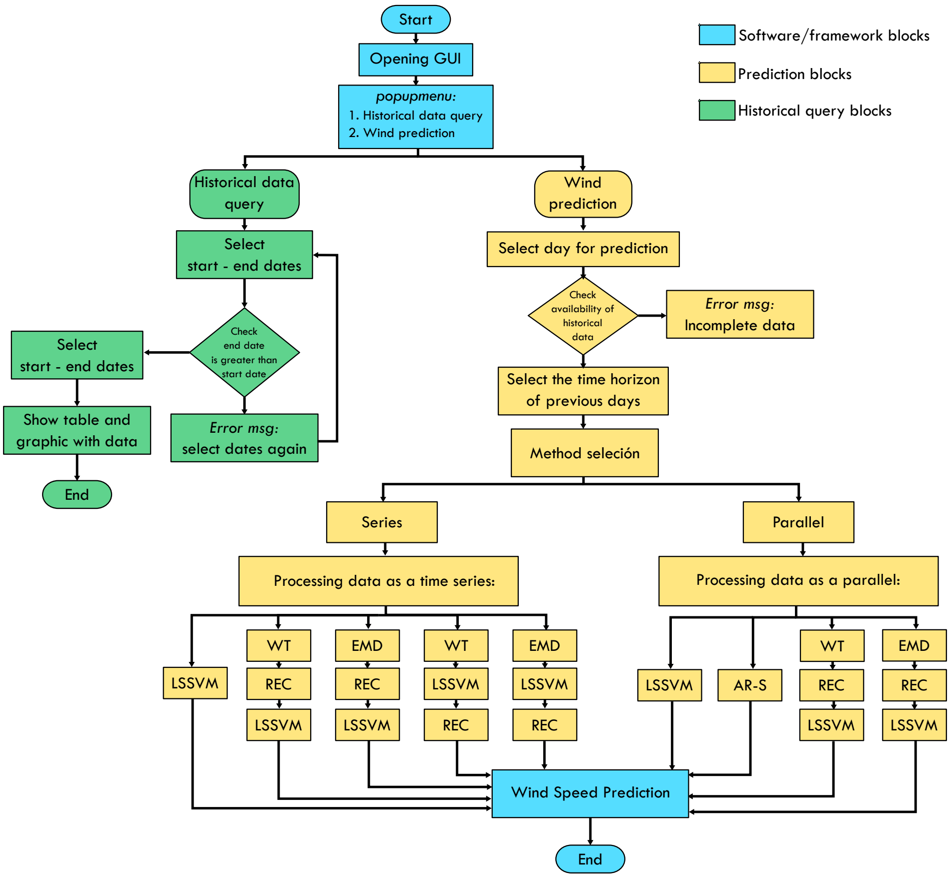

Figure 2. Flowchart for software tool developed.

[19]. WT is carried out using a function called *mother wavelet*, $\Psi(t)$, with *mother wavelet* the signal of interest is split down in terms of different frequencies that make up a family of functions that are translations and expansions of the mother wavelet, represented as $\Psi_{a,b}(t)$, where b performs the translation and a expansions or scales (Eq. 1).

$$\Psi_{a,b}(t) = \frac{1}{\sqrt{a}}\Psi\left(\frac{t-b}{a}\right) \quad a > 0; a, b \in \mathbb{R} \tag{1}$$

Continuous Wavelet Transformation of a function of interest is obtained by Eq. 2. Where $\Psi^*(t)$ is the conjugate complex of $\Psi(t)$. However, the continuous form contains a lot of redundant information. Thus, the use of the Discrete Wavelet Transform (DWT) is implemented [20]. DWT uses both the scaling and the translation parameter, values proportional to powers of 2. DWT allows a multi-resolution analysis (MRA). MRA can be seen as the process of passing the signal of interest through a low pass filter and a high pass filter. The output of the low pass filter is called *approximation*, while that of the high pass filter, *detail*. When the decomposition is done for multiple levels, the approach signal decomposes again into two subcomponents of low and high frequencies Figure 3.

$$C(a,b) = \frac{1}{\sqrt(a)}\int x(t)\Psi^*\left(\frac{t-b}{a}\right) dt \tag{2}$$

Gómez-Luna et al [21] quantified the energy dispersion in the frequency of a large set of wavelets as a function of the number of coefficients of the filter that implements the decomposition. The result is that the *Daubechies* family has the smallest dispersion when the filter length is even, compared to other families such as symmlets, coiflets, biortogonal and inverse biortogonal.

For the prediction of the wind speed, a Wavelet decomposition is performed using the mother Wavelet *Daubechies* 3, which produces an equivalent filter of 6 coefficients. Besides, a decomposition is

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performed in 5 levels, that is, 5 detail signals and 1 approach signal. Multiple prediction experiments support the level of decomposition selected, as well as the choice of the mother Wavelet. In the reconstruction of the filtered signal, one or more high-frequency components are neglected. High-frequency components contain information mostly of variability inherent in the wind speed and not of its tendency.

Figure 3 shows a wind speed signal for 120 hours (5 days), and for its components after applying the DWT with the command *waverec* of the MATLAB® tool, for 5 levels (five detail components in decreasing order of frequencies, and an approximation component). Mother Wavelet *db3* was implemented. The actual wind speed performance in that time and the reconstruction of this signal when the higher frequency component is neglected are shown in the first box. Note that even by neglecting the detail component of higher frequencies (d_1^5), the reconstruction looks very similar to the original signal.

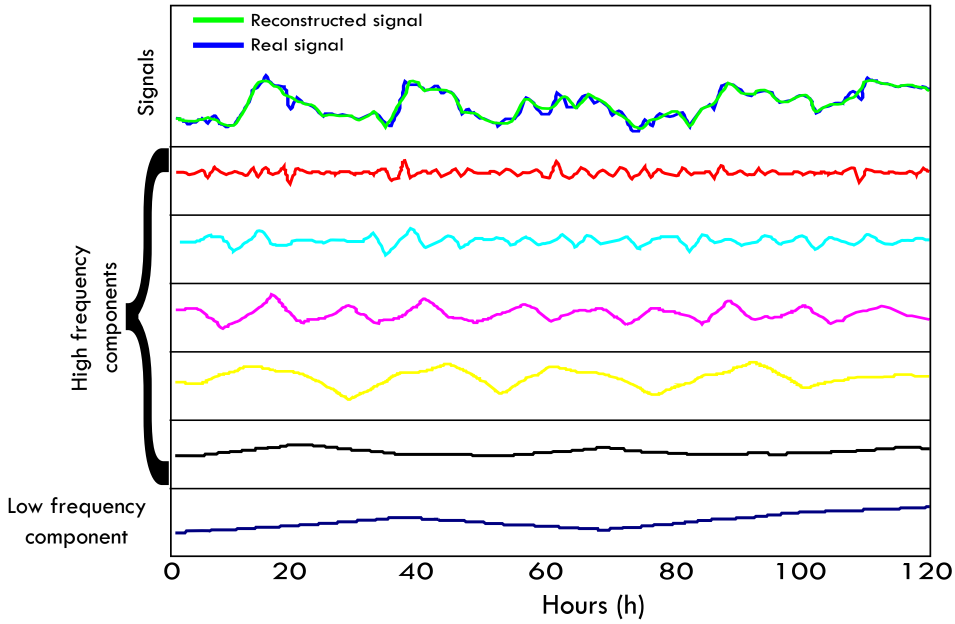

Figure 3. Discrete Wavelet Transform Decomposition Level.

2.2. *Empirical Mode Decomposition (EMD)*

According to [22] EMD is applied to analyze signals rather than to predict them. Particularly, atmospheric signals have a high correlation linking them where EMD is useful. The objective of this technique is to decompose non-stationary and/or non-linear signals, in order to convert them into a series of stationary signals (Eq. 3). Where n is the number of empirical modes in which the original signal decomposes. In this specific case the wind speed signal. C_i is the component that is obtained from the decomposition of the signal in functions of intrinsic mode (IMF) and r_n is the high-frequency residue [23].

$$X(t) = \sum_{i=1}^{n} C_i + r_n \tag{3}$$

2.3. *Least Square Support Vector Machine (LSSVM)*

LSSVM is properly related to classification and regression problems. Given a set of training examples (samples), we can label the classes and train an LSSVM to build a model that predicts the class of a new sample. LSSVM is a model that represents the sample points in space, separating the

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classes by a hyperplane as wide as possible. New samples are set in correspondence with the model, depending on their proximity [24].

For Method II and Method IV An analysis of historical wind speed data reflects its non-linearity. For this reason, historical data were taken and divided as time series using the Wavelet transform algorithm; then the details or components that contributed greater randomness to the series were discarded, and finally the LSSVM model was used to predict the 24 hour periods of one day [24,25]. The goal of the LSSVM model is to minimize the penalty error that arises from the regression. This penalty error is denoted as C and is shown in Eq. 4 [26].

$$C = \frac{1}{2}\omega^T\omega + \frac{1}{2}\gamma\sum_{i=1}^{N}\xi_i \tag{4}$$

$$\text{s.t.} : y_i = \omega^T\phi(x_i) + b + \xi_i,\ i = 1, ..., N \tag{5}$$

3. Test and results

To evaluate the prediction techniques implemented, historical records of wind speeds were used. The records contain hourly wind speed information for each day of a year. For this data set, the prediction techniques that were processed in the computational tool were evaluated (Figure 4). The metric used to measure the performance of each prediction technique is the mean square error. Mean square error is equal to the standard deviation when the average of the errors is small and the number of samples is large.

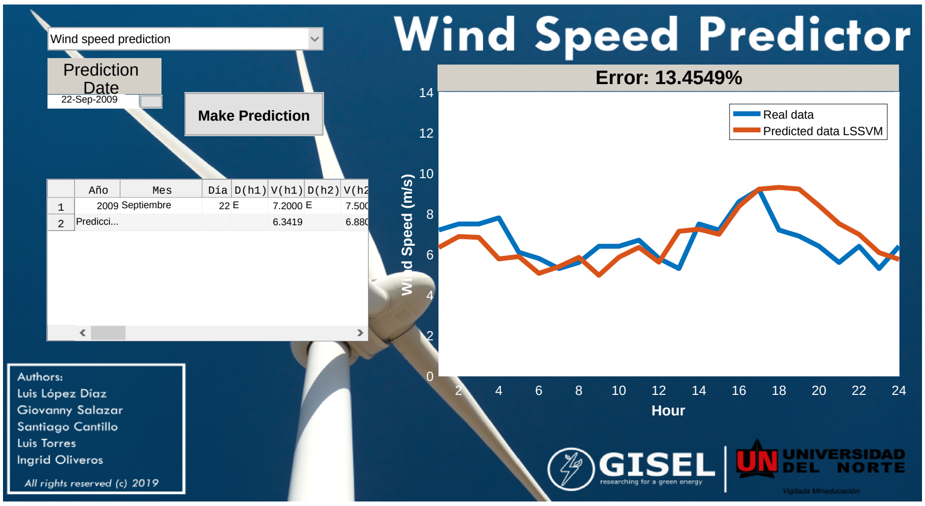

Figure 4. Graphical interface for wind prediction.

To predict with a filter with serial data, the n days before the one being predicted are taken, a vector is constructed with all the data as a continuous signal, and the next 24 points of that are predicted. For the preparation of serial data, 5 possible methods are designed (Figure 5a). To predict with a mathod with parallel data, the n days before the one being predicted are taken, 24 vectors are constructed with each hour of those n days. For example, by 7 o'clock a wind speed vector of those n days is built at 7 in the morning. With each of these vectors, the same time of the specific day selected is predicted. Four possible methods are designed for parallel data group (Figure 5b).

Initially, of the nine prediction methods implemented, the five best cases were selected. This previous selection of methods was made based on the histograms of the prediction errors. In Figure 6, the histograms obtained for each method are shown. Histograms discard those that have a platykurtic form, that is, they have the greatest standard deviations. From the above selection leads us to evaluate in detail the following methods:

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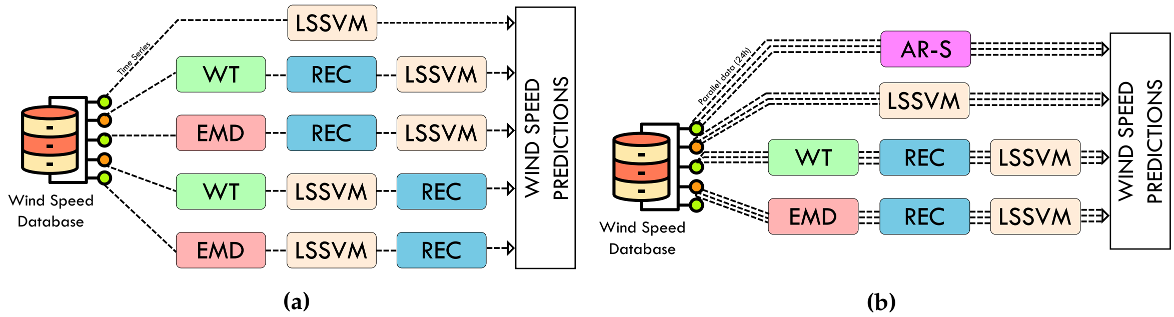

Figure 5. Prediction methods implemented. (a) Series. (b) Parallel.

Series methods:

- Method I: LSSVM
- Method II: WT-LSSVM-REC

Parallel methods:

- Method VI: Autoregressive simple
- Method VII: LSSVM
- Method VIII: WT-REC-LSSVM

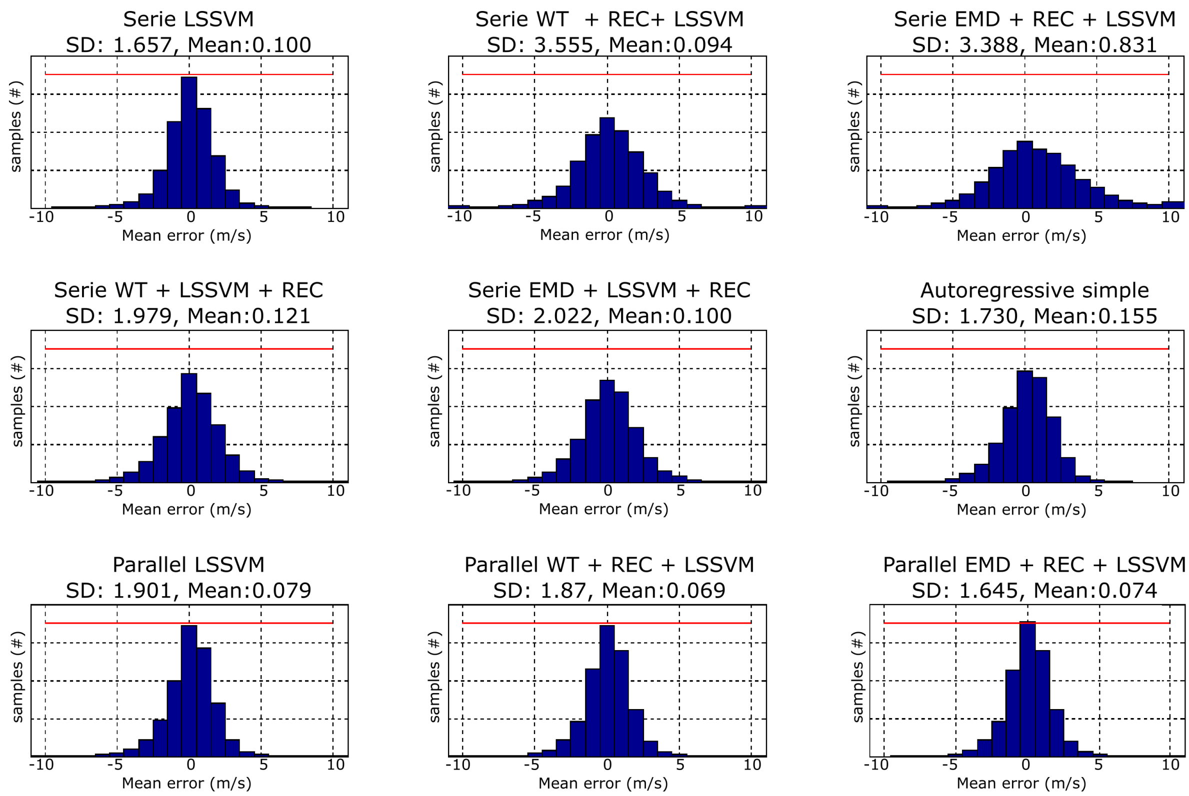

Figure 6. Histograms for the nine prediction methods.

To calculate the mean square error of the five selected methods, the next windy day (24 hours) was predicted using a set day horizon. This experiment was performed 30 times with randomly selected days from the historical record. The error is calculated from the difference in the predicted value with the actual value of the wind speed. For each of the prediction techniques, the mean square error is calculated by varying the horizon of days used in the prediction. In Figure 7a the mean square errors obtained for the prediction techniques are presented varying the horizon of days used from 14 to 35.

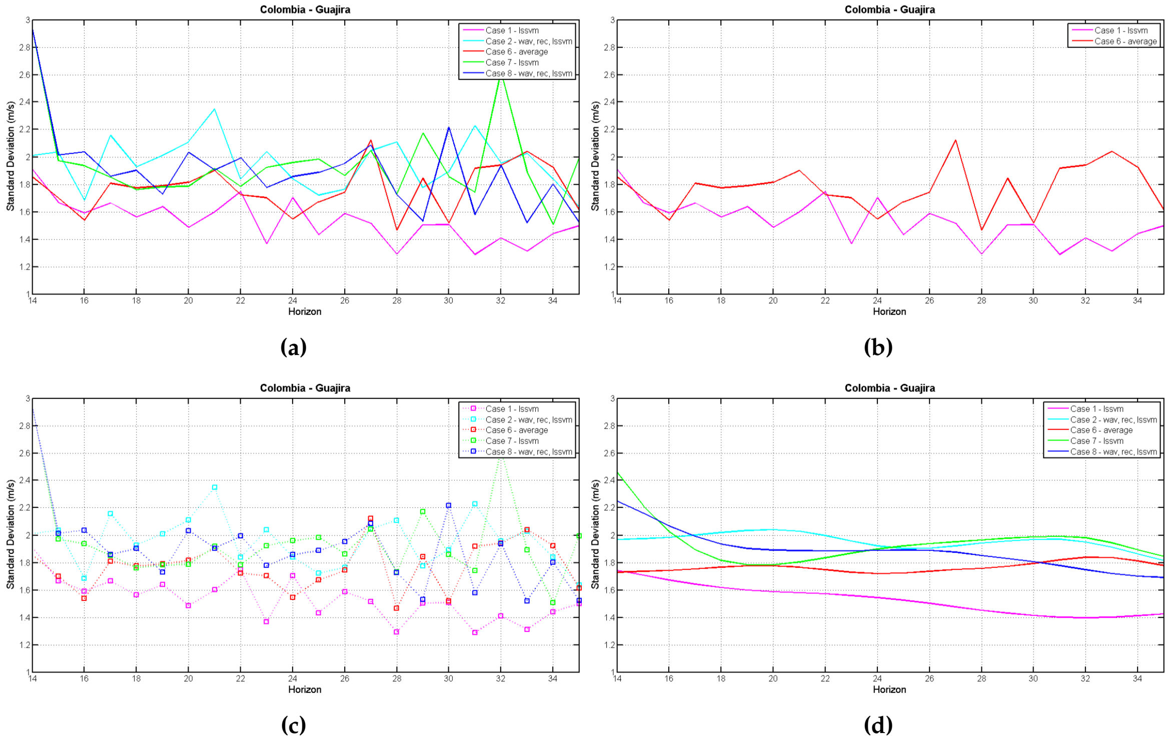

Figure 7. Mean square error for different horizons. Puerto Bolivar (Colombia).

From Figure 7a it can be concluded that the support machine Vector (LSSVM) and simple average (Autoregressive simple) are the prediction techniques that have a lower error.

To make the comparison between the two better curves easier for the reader, Figure 7b is presented with the results obtained for the LSSVM and the simple average. It is visible that initially both the simple average and the LSSVM have a comparable mean square error. However, as the horizon of days used increases, LSSVM has lower prediction errors than the simple average.

The mean square errors are values that are calculated for each specific day horizon. Being a set of discrete values a continuous plot may be a bit arbitrary. This is why in Figure 7c discrete points are shown joined by a dotted line that suggests a trend. To show the trend that MSE (Mean Square Error) follows in prediction techniques, a curve adjustment is made to each technique. The curve fit used is smoothing spline with a *smoothing factor* of 0.07. The curve adjustment described previously is shown in Figure 7d.

In addition to the site in La Guajira (Colombia), the same experiment was carried out for two sites located in the Galapagos Islands (Ecuador) and the Port of Santa María (Spain). The conclusions that were obtained in these different places follow the same statements that was obtained for the Colombian site. Figure 8 and Figure 9 show the results obtained for the locations in the Galapagos Islands and the Port of Santa María.

From the tests and results it can be determined that the method of least average square error is LSSVM. To illustrate the prediction made by the LSSVM method on a given day, a prediction of the following 24 hours is made. Figure 10 shows the values predicted by the LSSVM in green and the actual wind values for that particular day in the black.

4. Conclusions

Historical wind speed data measured at three locations were used. The selected sites are monitored by weather stations that supply the wind speed database with the average hourly data. Besides, three non-parametric statistical techniques were implemented to perform wind prediction. The least-squares support vector machine, Wavelet Transform (WT) and Empirical Mode Decomposition (EMD) were

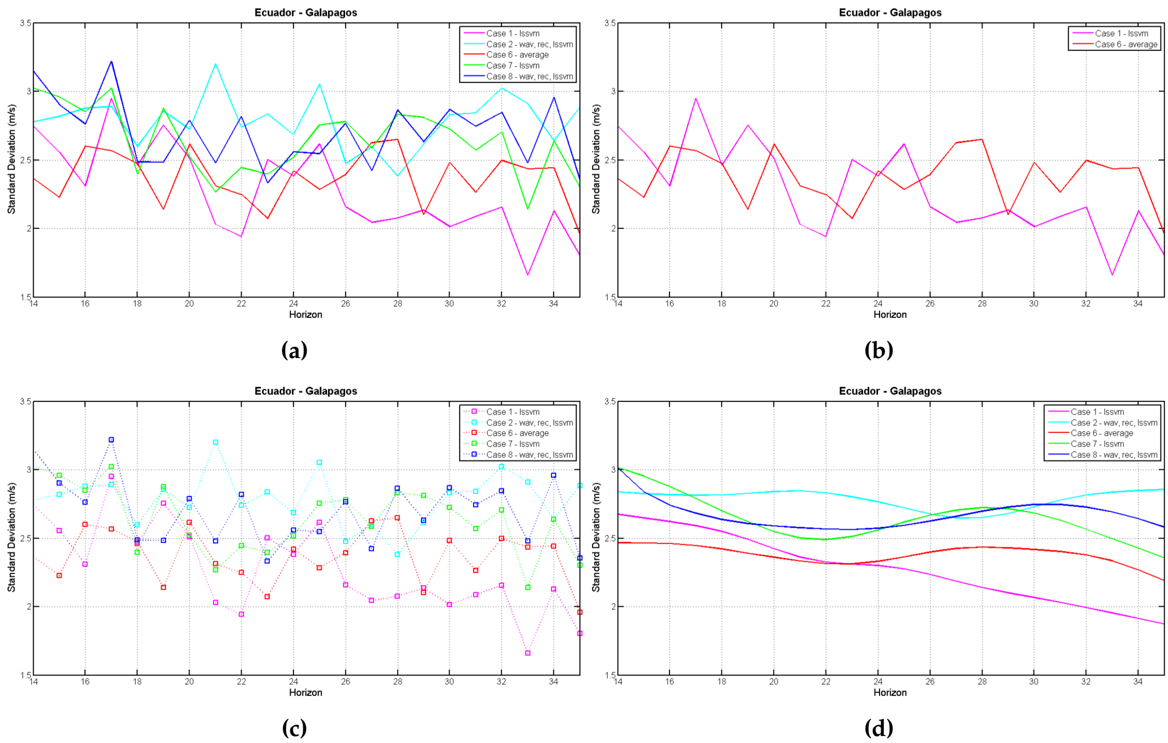

Figure 8. Mean square error for different horizons. The Galapagos Island (Ecuador).

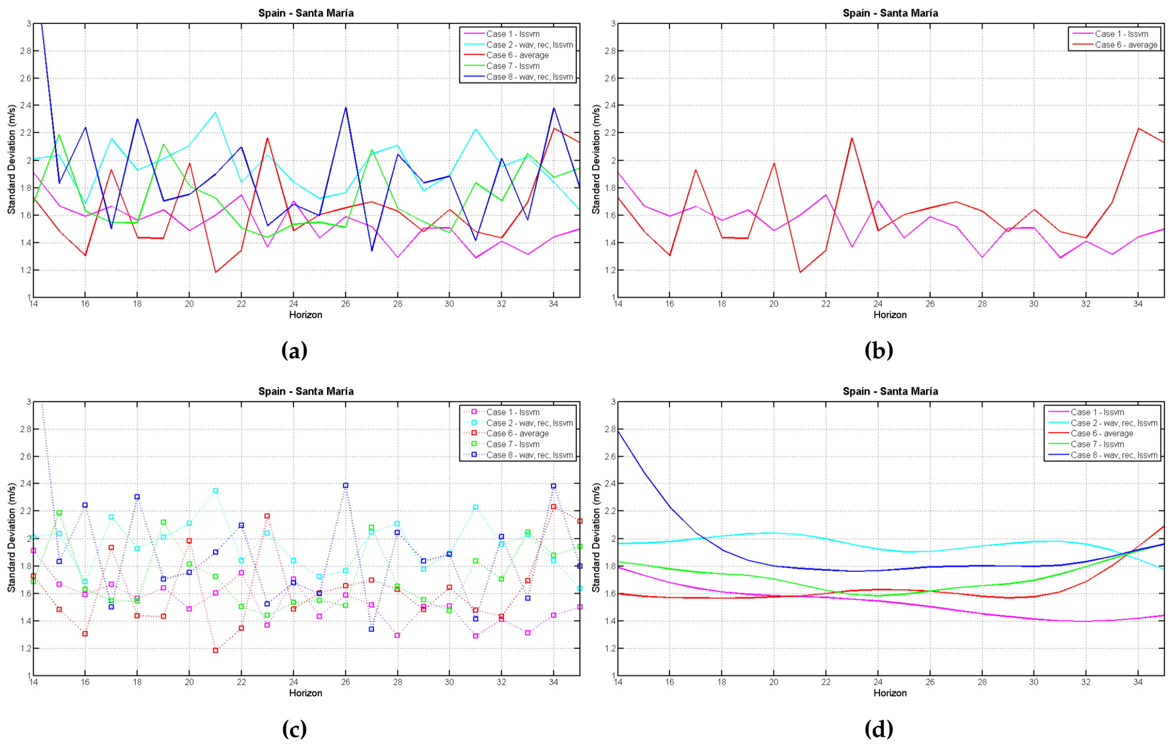

Figure 9. Mean square error for different horizons. Port of Santa Maria (Spain).

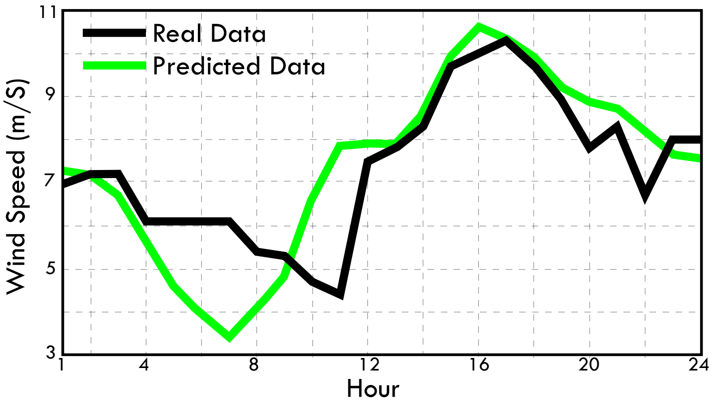

Figure 10. Day-ahead prediction using LSSVM for a typical day.

implemented. WT and EMD were used as signal decomposition tools to eliminate the high-frequency variability of the wind speed signal and obtain the trend that is the variable of interest.

Combinations were made between the techniques implemented seeking an improvement in the accuracy of the prediction values obtained. Nine prediction methods were implemented based on the program techniques. Five of these techniques make a time series treatment of wind data. Four of them make a parallel treatment of the prediction hours. From the implemented framework, it was concluded that parallel techniques generally have better wind prediction performance.

The mean square error metric was used to compare the performance of the prediction methods. The mean square error is measured after a sampling block of randomly selected day predictions. It was obtained that the two best prediction techniques for different time horizons (previous days took to make the prediction) were the LSSVM as a time series and the simple Autoregressive model as a parallel time prediction. For the LSSVM method, the lowest mean square errors were obtained in the time horizons between 25 and 30 days, achieving standard deviations of up to 1.2 m/s.

As for recommendations and future work it is suggested to incorporate new meteorological variables such as temperature, atmospheric pressure, and air density. The meteorological variables have a correlation between them that can improve the wind predictions that are obtained for the next day. On the other hand, it is recommended to explore larger time horizons to determine a substantial improvement in the quality of the wind forecast. Increasing the horizon of data taken as historical also increases the computational cost and the execution time of the implemented methods.

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