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Research Article

Longitudinal Wind Speed Time Series Generated with Autoregressive Methods for Wind Turbine Control

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ABSTRACT. Although there are a wide variety of applications that require wind speed time series (WSTS), this paper emphases on WSTS to be used into wind turbine simulation for controllers tuning. These simulations involve several WSTS to perform a proper assessment. These WSTS must assure specific wind speed variations such as wind gusts and include some rare events such as extreme wind situations. The architecture proposed to generate this WSTS is based on autoregressive models with specific post-processing. The methodology used is entirely described by precise notation as well as it is parametrised using data gathered from a weather station. Also, specific parameters of this methodology are adjusted using features extracted from Extreme Operation Gust (EOG). Two different cases are performed and assessment; the first case is fed by weather data with high wind speed and significant variability. The second case, on the opposite, use moderate wind speed as a data source. Through final assessment, it shows that this methodology generates representative WSTS with realistic variations of wind speed.

Keywords: wind speed, time series, autoregressive models, wind turbine.

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1. Introduction

Wind is air in motion initially produced by the effect of the non-uniform distribution of sunlight on Earth surface due to Earth movements: the ecliptic trajectory around the Sun and perpendicular rotation around its axis. Sunlight is absorbed in several grades depending on Earth location. These effects produce bulk air movements because of variations of temperature, pressure, and composition at different atmospheric layers. Wind speed is a variable and uncontrollable factor. This factor is studied over an extended period by climate sciences and predicted by Weather forecasting.

There are various and diverse type applications that require a large chain of consecutive WSTS. The purpose of these applications can divide into two. On the one hand, for simulation analysis, different and variable kind of simulations are needed to assess rare events such as extreme wind situations when parameters of the control system are tuned(González-González et al. 2014). Also, another case of simulation analysis resides on capture under the wind speed conditions specific state occurs. For instance, detect the turbulence intensity threshold of wind when the initial fracture occurs in a fatigue simulation analysis (Li et al. 2018).

On the other hand, for forecasting purposes, predicting accuracy efficiently the short-term is crucial such as safety perform an operation and management of wind turbines (Sun et al. 2018). Also, wind power forecast to maintain a balance maintained between electricity consumption and generation is another situation of WSTS is used (Guo, Gao and Wu 2017).

Although there are diverse methods to generate WSTS, the primary classification divides method into deterministic and probabilistic approach such as Monte Carlo method (Guerrero et al. 2011).

A WSTS probabilistic model includes random variables and probability distributions which can reproduce the wind speed features. Weibull distribution and Rayleigh distribution are widely used (Sedaghat et al. 2017). However, the time evolution characteristics of wind speed are neglect in these probabilistic models (Guo et al. 2017). Modelling longitudinal wind speed is approached by several authors in different disciplines. A methodology for the simulation of bivariate non-stationary WSTS and direction was proposed (Solari and Losada 2016). A wind speed model considering meteorological conditions and seasonal variations, based on the Markov Chain, was proposed (Guo et al. 2017). A variogram function employed

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to measure the change rate exists between wind speed variations, and daily periodicity was proposed (Liu et al. 2016).

A deterministic wind speed model for forecasting using a combination of two methods: and time-varying mixture copula function (Gualtieri and Secci 2014) and outlier robust extreme learning machine (Peng et al. 2017).

This paper presents a framework to generate customised longitudinal wind speed time series for wind turbine controllers intended for simulation purposes using autoregressive methods. This customisation resides on using the data gathered from a specific weather station where wind turbine could place. Customised wind speed time series involve a better parametrisation of wind turbine controller due to increasing the accuracy between of real wind speeds and WSTS used in simulations. Autoregressive methods are powerful techniques to create time series in a stochastic way. Also, a post-processing data is carried out by a filter to wipe non-desired wind speed fluctuations.

This paper contains five sections organised as follow. Section 2 provides background information about the mathematical components used as well as the methodology applied to generate WTTS. Section 3 shows the sources from data is gathered. Section 4 presents the simulations performed using the methodology proposed and data parametrised. Section 5 brings main conclusions as well as future work planning.

2. Methodology

WSTS for simulation purposes, specifically for wind turbine control, is generated using the architecture presented in Figure 1. This model is fed by data gathered from a weather station as well as specific features of wind gusts. Although data sample is generated by the autoregressive model in a particular organised and random approach, a post-data-process is executed by filter and saturation blocks due to erase improper wind speed behaviour.

This section is organised as follows. The autoregressive component proposed as well as a short overview of autoregressive models are explained in Section 2.1. The post-data-process component to remove unwanted wind speed behaviour is explained in section 2.2.

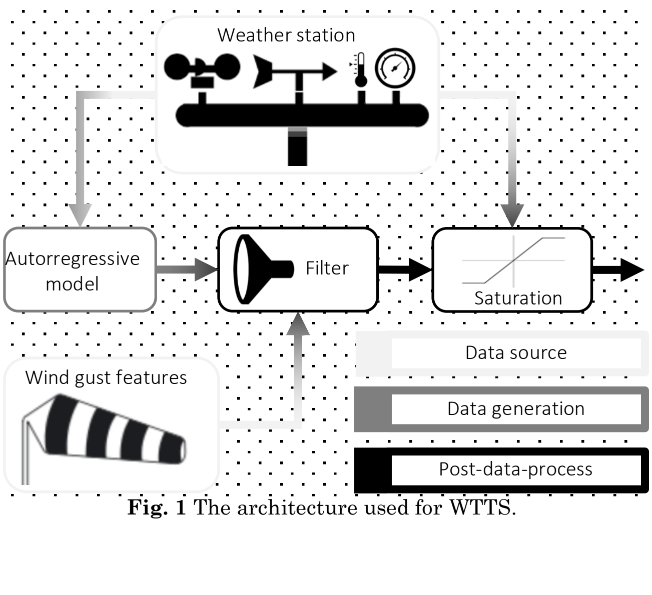

Fig. 1 The architecture used for WTTS.

2.1 Autoregressive models

An autoregressive model is a stochastic method to successively generate values of the specific variable based on its previous values (Durán Mario, Cros and Riquelme 2007). These models are used to perform different types of applications such as predictions (Durán Mario et al. 2007) and simulations that involve wind speed time series (Lojowska et al. 2010). An autoregressive model with p parameters is denoted by AR(q). Eq.(1) shows an AR(q) to produce a wind speed time series where v(t) is the wind speed at time t, c is a constant, φ_i is the $i-$th autoregressive parameter, and $\varepsilon(t)$ is an independent random normal distribution with zero mean and constant variance $\sigma_\varepsilon{}^2$, mathematically denoted as $\varepsilon(t) \sim N(0, \sigma_\varepsilon)$.

$$v(t) = c + \sum_{i=1}^{i=p} \varphi_i \cdot v(t-i) + \varepsilon(t) \qquad (1)$$

Parameters can be established by fulfilling statistics properties. On the one hand, the expected value properties are applied over Eq.(1) to obtain Eq.(2): i) The expected value at each instant is the same for the entire time series, and it corresponds with the mean value of entire time series, denoted by $\bar{v}$; ii) The expected value of autoregressive parameters and constant parameter are equal to themselves; iii) The expected value of a random normal distribution with zero mean and constant variance is zero.

$$\bar{v} \cdot \left(1 - \sum_{i=1}^{i=p} \varphi_i\right) = c \qquad (2)$$

On the other hand, the expected variance and auto-covariance properties are applied over Eq.(1). Auto-covariance is the covariance of the same time series separated by k instants, and it is calculated by Eq.(3). The variance of time series is a case of auto-covariance when there is no instant separated.

$$C_{vv}(t,k) = E[v(t) \cdot v(t-k)] - E[v] \cdot E[v] \qquad (3)$$

Using applying the premise of the expected variance and auto-covariance at each instant is the same for the entire time series to Eq. (1) gives a system of linear equations of p autoregressive parameters and p linear equations represented by Eq.(4).

$$\begin{bmatrix} C_{vv}(t,1) \\ \vdots \\ C_{vv}(t,p) \end{bmatrix} = \begin{bmatrix} var(v) & \cdots & C_{vv}(t,p-1) \\ \vdots & \ddots & \vdots \\ C_{vv}(t,p-1) & \cdots & var(v) \end{bmatrix} * \begin{bmatrix} \varphi_1 \\ \vdots \\ \varphi_p \end{bmatrix} \qquad (4)$$

To calculate AR(p) parameters. Firstly, the p autoregressive parameters are settled by Eq.(4) and secondly constant parameter is settled by Eq.(1).

There are variations of the preliminary AR(q) model by adding one or more components. One case is the autoregressive moving average model that includes a second polynomial for the moving average to smooth short-term fluctuations.

An autoregressive moving average model with p parameters of autoregression polynomial and q parameters of moving average polynomial is denoted by ARMA(p, q). Eq.(5) shows an ARMA(p, q) model to produce a wind speed time series where θ_i is the $i-th$ parameter of the model. Polynomial parameters can be calculated using least squares technique (Lojowska et al. 2010), Burg Method (Rajagopalan and Santoso 2009) and Shanks method (Rajagopalan and Santoso 2009).

$$v(t) = c + \sum_{i=1}^{i=p} \varphi_i \cdot v(t-i) + \sum_{j=1}^{j=q} \theta_i \cdot \varepsilon(t-j) + \varepsilon(t) \tag{5}$$

Another autoregressive model combining ARMA(p, q) model with an integral component is an autoregressive integrated moving average model. This model is denoted by ARIMA(p, d, q) with d difference instant

Another autoregressive model used when some statistics parameters (such as mean and variance) change over time is Autoregressive Integrated Moving Average (ARIMA) model. This model adds a component with d parameters of moving average polynomial, and it is denoted as ARIMA(p, d, q) (Drobinski 2012). Making a comparison with the previous models, on the one hand, ARMA(p, q) model is a particular case of ARIMA(p, d, q) when there is not integration polynomial ($d = 0$). On the other hand, AR(q) is a particular case of ARIMA(p, d, q) when there is neither integration polynomial ($d = 0$) nor autoregression polynomial ($p = 0$) (Cadenas and Rivera 2010)

An alternative variation of autoregressive model is via including autoregressive conditional heteroskedasticity models. In this type of models, the random variable variance value is not constant, and it is adaptable using a function of the previous terms. For example, generalised autoregressive conditional heteroscedasticity models use an additional autoregressive model to calculate the random variable variance value (Hamilton and Susmel 1994). The heteroscedasticity component improves wind speed time series due to the capability of modelling together moments with high variability combined with little variation (Lojowska et al. 2010).

2.2 Post-data-process

Enhance certain features of the autoregressive sampled signal through a set of mathematical operations is needed by using a digital filter to removes unreal high fluctuations of wind speed. Although there are different types of filters according to the frequency response, a second order low pass filter is proposed to avoid high variations between two consecutive wind speed points. This filter is described in Laplace notation as:

$$\frac{V_2(s)}{V_1(s)} = \frac{{\omega_n}^2}{s^2 + 2 \cdot \xi \cdot \omega_n \cdot s + {\omega_n}^2} \tag{6}$$

where s is the Laplace transform variable, ζ is the damping ratio and ω_n is the natural frequency in rad/s. These values are settled as following. On the one hand, the natural frequency is assigned according to cut-off frequency desired by using Eq(7) where f_n is the cut-off frequency. Frequencies above cut-off are reduced by 40 dB/dec.

$$\omega_n = 2 \cdot \pi \cdot f_n \tag{7}$$

On the other hand, damping ratio defines the overshoot of the response. This overshoot is defined as the maximum peak value of the response curve measured from the desired response of the system. Normally, it is given in the range between 0 and 1 and calculated by Eq(8) where M_p is the overshoot response in parts per unit.

$$M_p = e^{-\left(\xi / \sqrt[2]{1-\xi^2}\right)} \tag{8}$$

The attenuated frequencies are represented by Figure 2and Figure 3. These figures use a logarithmic scale. The first shows the magnitude of the frequency response in decibels. The second shows the phase shift in radians.

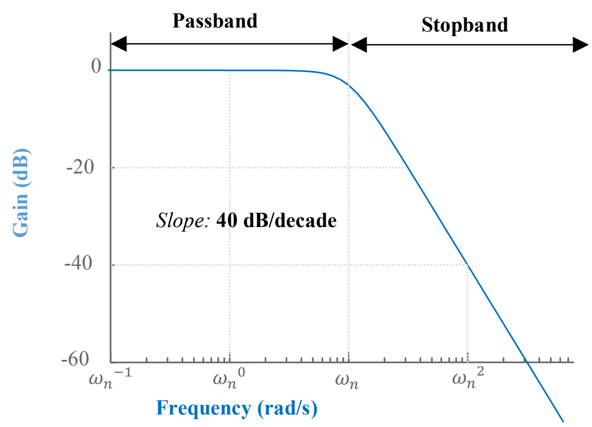

Fig. 2 Magnitude attenuation at each frequency.

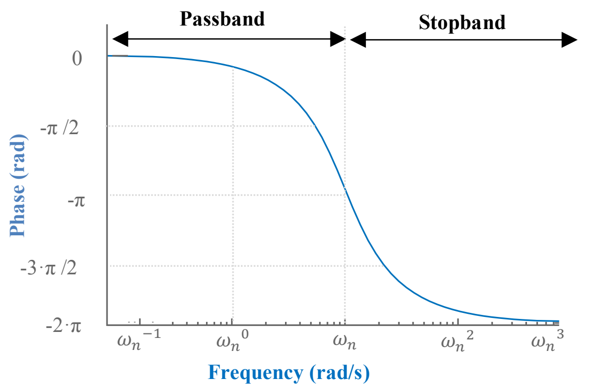

Fig. 3 a) Magnitude attenuation at each frequency. b) Phase at each frequency response.

2.3 Saturation block

The saturation block limits range of wind speed values fluctuates. This range is defined by Eq(9) with the wind speed lower limit and upper limit parameters.

$$v_{min} \le v_1 \le v_{max} \tag{9}$$

3. Case study

3.1 Weather station

Data collected was from a weather station placed inside of Vitoria-Gasteiz, the capital city of Basque country, thanks to Basque Meteorology Agency Euskalmet. The exact location of this weather station is at -2.68899 and 42.8604 of longitude and latitude values respectively. The location of the weather station is 546 meters above sea level, and sensors installed are 11 meters above the ground. Figure 4 shows two photos about this weather station and the place that it placed.

Fig. 4 Weather station placed in one street of Vitoria-Gasteiz.

Table 1
Data gathered from the weather station.

Symbol	Description	Units
t	It is the timestamp that identifies uniquely date and time of event occurred.	yy-mm-dd hh:mm
$\bar{v}_n$	It is a statistical longitudinal wind speed averaged over a period of 10 minutes expressed in meters per second.	(m/s)
v_{max}	It is the maximum longitudinal wind speed over a period of 10 minutes expressed in meters per second.	(m/s)
v_{min}	It is the minimum longitudinal wind speed over a period of 10 minutes expressed in meters per second.	(m/s)
S_n	It is a standard deviation of wind speed over a period of 10 minutes expressed in meters per second.	(m/s)
T	It is a statistical air temperature averaged over a period of 10 minutes expressed in Kelvin degrees.	(K)
H	It is a statistical relative air humidity averaged over a period of 10 minutes expressed as a percentage.	(%)
P	It is a statistical atmospheric pressure over a period of 10 minutes expressed in Pascal.	(Pa)
z	It is the meters above sea level.	(m)

Source: www.euskalmet.euskadi.eus

Although this weather station can provide several public records, the only information used is shown in Table 1. Every 10 minutes, a data sample is stored.

3.2 Air density

Air density fluctuates with temperature, pressure and humidity. However, according to International Electrotechnical Commission (IEC), WSTS are expressed with normalised value of air density at 1.225 kg/m^3. This value is presented at sea level pressure and 288.15 K temperature according to the international standard atmosphere. Air density is denoted as ρ_{Air} moreover, expressed regarding pressure and temperature by Eq(10) where g is the gravity constant (9.81 m/s^2 at sea level) and R is the specific gas constant for air (287.05 J/(kg · K)). This equation combines ideal gas law equation as well as constant pressure at sea level, p_0, relates to its exponential decrement as height increases. The height above sea level is denoted by z.

$$\rho_{Air} = \frac{p_0}{R \cdot T} \cdot exp\left(-\frac{(g \cdot z)}{(R \cdot T)}\right) \tag{10}$$

Additionally, air density can be calculated more accurate according to the International Committee on Weights and Measures using temperature, pressure and humidity. WSTS with normalised value of air density require postprocessing consisting of divide WSTS generated by the normalised air density and multiplied by air density, calculated at each time, using Eq(10).

3.3 Auto-covariance

The autoregressive block is parametrised with longitudinal average, auto-covariance and standard deviation wind speed. The average and the standard deviation over a period of 10 minutes is gathered directly from the weather station. However, auto-covariance values must be settled experimentally due to the frequency of the sample of the weather station is fewer than the frequency required to generate WSTS. Usually, for simulation purposes, the frequency required is less than a second (González-González et al. 2014).

Extract features set the maximum values of the auto-covariance from a deterministic wind gust called Extreme Operation Gust (EOG). The IEC 61400 norm defines this gust, and a wind speed decrement characterises it, following a high increment as a Mexican hat wavelet. The maximum auto-covariance values are calculated by

$$Cmax_{vv}(k) = \frac{d^k}{dt^k} v_{EOG}(t) \tag{11}$$

Where $Cmax_{vv}(k)$ is the maximun auto-covariance value of the WSTS separated by k instants and $v_{EOG}(t)$ is the EOG function.

3.4 Cut-off frequency

Similarly, cutoff frequency parameter is settled by an EOG characteristic time parameter defined in the norm as 10.5 seconds. The Cutoff frequency parameter is calculated by the inverse value of EOG characteristic time represented by Eq(12)

$$f_n = 10.5^{\ -1} \tag{12}$$

3.5 Wind speed boundaries

The saturation block is settled by maximum longitudinal wind speed values from the weather station. Due to nonpositive values does not make sense, the minimum longitudinal wind speed is defined by zero.

$$v_{min} \geq 0 \tag{13}$$

4. Simulations and results

4.1 Simulations

Although several simulations are performed, only the two main representative simulations are shown in this paper. The first simulation is generated by data gathered from the weather station on February 13, 2017. The data of the first 4 hours of this day are shown in table 1; an average high wind speed characterises it.

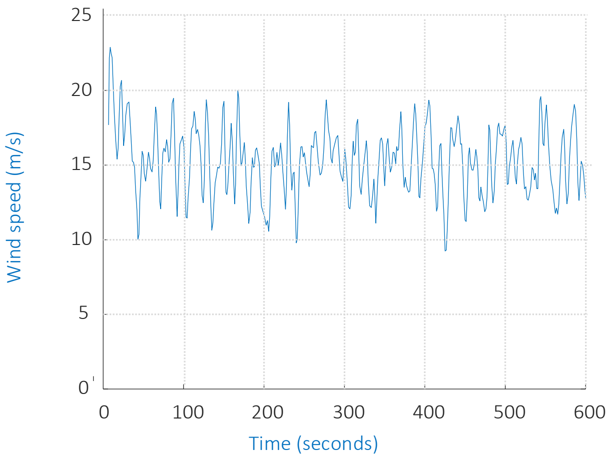

Fig. 5 10 minutes of WSTS with data gathered on February 13, 2017.

Table 1
Data gathered from the weather station on February 13, 2017.

Time interval		$\bar{v}_n$	v_{max}	S_n	T	H	P
0:00	0:10	14.2	23.7	3.3	284.1	71.0	93780
0:10	0:20	13.6	24.7	4.0	284.2	71.0	93780
0:20	0:30	13.5	26.8	4.7	284.1	72.0	93770
0:30	0:40	14.7	25.4	4.1	284.1	72.0	93750
0:40	0:50	15.4	25.5	3.9	284.0	73.0	93720
0:50	1:00	13.0	29.0	4.4	284.0	73.0	93720
1:00	1:10	12.8	27.1	4.6	284.1	72.0	93740
1:10	1:20	13.1	30.6	5.3	284.1	72.0	93750
1:20	1:30	12.8	24.9	3.8	284.2	71.0	93760
1:30	1:40	10.9	22.6	4.0	284.1	72.0	93760
1:40	1:50	13.9	30.2	4.6	284.1	72.0	93760
1:50	2:00	13.3	24.5	4.8	284.1	72.0	93760
2:00	2:10	11.9	29.3	5.4	284.1	72.0	93780
2:10	2:20	11.4	26.7	4.8	284.1	72.0	93770
2:20	2:30	15.0	27.9	5.0	284.0	73.0	93720
2:30	2:40	13.1	22.6	4.1	284.0	73.0	93720
2:40	2:50	14.8	28.8	4.2	284.0	72.0	93710
2:50	3:00	10.3	22.3	4.3	284.0	73.0	93750
3:00	3:10	10.4	22.3	3.7	284.0	72.0	93770
3:10	3:20	11.6	26.6	5.1	284.2	70.0	93770
3:20	3:30	12.1	25.6	3.8	284.3	69.0	93790
3:30	3:40	11.9	27.1	4.2	284.2	69.0	93790
3:40	3:50	11.2	22.9	3.7	284.0	70.0	93790
3:50	4:00	12.2	23.4	3.5	284.1	69.0	93770
4:00	4:10	12.0	23.5	3.9	284.2	68.0	93770

Figure 5 shows 10 minutes of the first simulation of WSTS using the data from Table 1 and the proposed method.

Table 2
Data gathered from the weather station on April 19, 2017.

Time interval		$\bar{v}_n$	v_{max}	S_n	T	H	P
0:00	0:10	2,6	4,1	0,7	282,8	61,0	95810
0:10	0:20	1,7	3,7	0,7	282,8	62,0	95820
0:20	0:30	2,1	3,5	0,7	282,6	61,0	95820
0:30	0:40	2,4	3,9	0,8	282,4	60,0	95820
0:40	0:50	2,7	4,5	0,9	282,3	60,0	95820
0:50	1:00	3,1	5,2	0,7	282,1	59,0	95820
1:00	1:10	2,8	4,8	0,7	281,9	58,0	95810
1:10	1:20	2,7	4,5	0,9	281,8	59,0	95810
1:20	1:30	2,8	4,3	0,7	281,6	59,0	95800
1:30	1:40	2,8	4,1	0,7	281,3	60,0	95800
1:40	1:50	2,9	5,0	0,8	281,1	59,0	95790
1:50	2:00	3,4	5,5	0,8	281,0	59,0	95780
2:00	2:10	3,5	4,7	0,7	280,9	59,0	95770
2:10	2:20	3,4	5,6	0,7	280,8	58,0	95780
2:20	2:30	3,0	5,2	0,9	280,8	57,0	95780
2:30	2:40	2,8	4,4	0,6	280,9	56,0	95790
2:40	2:50	3,0	4,2	0,6	280,7	56,0	95790
2:50	3:00	3,0	4,5	0,6	280,6	56,0	95790
3:00	3:10	2,9	4,4	0,6	280,6	55,0	95790
3:10	3:20	3,3	5,3	0,8	280,6	54,0	95790
3:20	3:30	3,2	5,3	1,0	280,7	53,0	95790
3:30	3:40	3,3	5,0	0,7	280,7	51,0	95790
3:40	3:50	3,4	5,1	0,8	280,7	51,0	95790
3:50	4:00	3,2	4,7	0,7	280,6	51,0	95790
4:00	4:10	3,0	5,0	0,7	280,4	51,0	95790

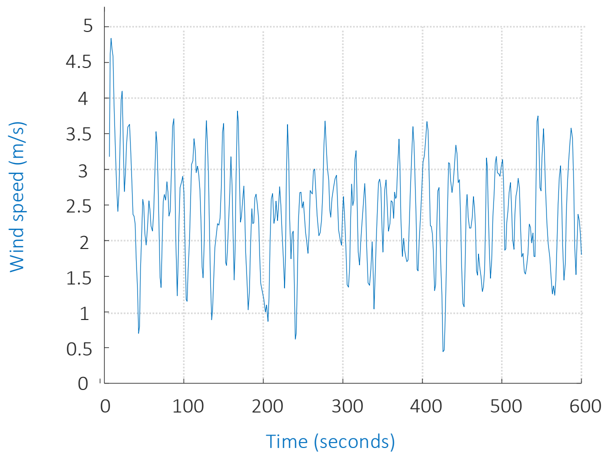

Fig. 6 10 minutes of WSTS with data gathered on April 19, 2017.

The second simulation represents the WSTS generated by data gathered from the weather station on April 19, 2017.

Moderate wind speed characterises this day. The data of the first 4 hours of this day are shown in table 2.

Figure 6 shows 10 minutes of the second simulation of WSTS using the data from Table 2 and the proposed method.

4.2 Results

The WSTS generated in figure 5 and 6 are appropriate to be implemented into simulations for wind turbine control. Tuning this controller by time response simulation require synthetic longitudinal WSTS as these cases presented.

The wind speed parameter inside simulations for wind turbine control is the primary disturbance parameter of the system. Generate realistic wind speed fluctuation in a short time is required to set suitable values on control parameters. Although the proposal digital-filter reduces unrepresentative high variations of wind speed, select the appropriate values is not trivial. According to simulations performed, the proposal of calculating the cutoff frequency parameter using extracting features from deterministic normalised wind gust is a correct strategy.

However, through a contrast between average and standard deviation used to parametrise the autoregressive model and the calculated over WSTS generated in figure 5 and 6, it shows a decrease in wind variability. This assessment is shown in the Table 3.

Although standard deviation error is significant, the maximum change rate of wind speed concerning time does not cross the autoregressive threshold defined.

Table 3
Average and standard deviation error.

Properties	Figure 5	Figure 6
Average error	0.20%	0.39%
Standard deviation error	41.32%	41.25%

Source: survey data

5. Conclusions

This paper presents a methodology to generate WSTS. This methodology is mainly composed of three elements: autoregressive model, filter and saturation block. Data gathered from a weather station parametrises the autoregressive model and saturation block. The filter is parametrised by analysing EOG characteristic time defined in the IEC 61400 norm.

This methodology is appropriate to implemented into time response simulations for tuning wind turbine controls due to short time wind speed fluctuations generated are particularly realistic. Wind turbine controllers are designed to reject wind speed disturbances. Therefore, unrealistic variations of wind speed must be avoided.

Two WSTS cases are generated with different data. They are shown in Figure 5 and Figure 6. Also, these two WSTS are evaluated by various statistic metrics to calculate the error performed from the initial data.

The standard deviation error resides on effect performed by filter component due to frequencies reduced decreases samples fluctuation. The Standard deviation error is very similar in both simulations, so in future work, another gain parameter will be needed to reduce the error commitment. A considerable amount of simulations will be performed to check gain parameter experimentally.

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