Onshore Wind Farms Maintenance Optimization Using a Stochastic Model

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Abstract

A specific feature of wind power generation is the stochastic behavior of wind velocity what determines the energy produced, and also influences the turbine degradation process due to the stochastic load suffered by the wind turbine. Thus, wind turbines present a degradation process more complex than the equipment that work under stationary conditions.The selection of maintenance strategy, that comprises the date to perform a maintenance activity, the maintenance frequency and the duration of such activity have a great influence on the operational cost, what determines the plant viability.

Wind velocity probability distribution can be obtained from daily wind data measuraments, and by Monte Carlo sampling, it is possible to estimate the power generated. This generation has an associated cost due to the loss of production during maintenance.This work is focused on finding the best maintenance strategy that minimizes the total cost and maximize the annual energy produced of a wind turbine considering as decision variable the maintenance frequency.

Keywords: Stochastic model, wind turbine, maintenance scheduled

1. Introduction

Wind power is regarded as a key technology to meet the planned targets of carbon emission reductions and the diversity of energy supply sources. During the last decade a rapid expansion of this energy technology has been observed. In Spain, wind capacity has increased form about 2000 MW in 2000 to 20000 in 2010, representing a 16% of the total capacity available to supply the electricity

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demand. With this scenario, wind power maintenance planning plays an important role in both, electric power supply scheduling and power generation costs [1]. The operational conditions of wind farms are quite different from traditional power stations. Thus, a specific feature of wind power generation is the stochastic behaviour of wind velocity, what determines the energy produced, and also influences the turbine degradation process due to the stochastic load suffered by the wind turbine[2][3]. Such loads influence the failure rate of wind turbine components accelerating the aging process. Nowadays, the maintenance plan scheduled in wind turbine farms include routine checks to minimize the degradation effects. Moreover, maintenance plan is determined by the meteorological conditions. In order to guarantee safety work conditions, maintenance activities can not be undertaken under adverse meteorological conditions. At first glance, the best option to perform maintenance activities is at wind velocities under 5 m/sec, as in this condition there is no energy production and the task is performed under safe conditions. Unfortunatelly, this situation is not always achieved, so maintenance tasks have to be planned to maximize the annual energy generated and minimize the costs associated.

Nowadays, there are several analyses focused on obtaining the maximum reliability level and identifying the optimal repair time based on the failures statistics. The Weibull distribution has been applied in many applications to model the life-time of a given system. For example, reference [5] models the failure of wind turbine components in order to estimate the parameters of the distribution and to establish the optimal replacement time for these components to minimize the total maintenance costs.

Reference [6], shows the degradation level depends on the climate characteristics (wind velocity, capacity factor, and temperature) under the wind turbine is operating. In this study, the failure rate is modeled as a Weibull distribution. Many studies used homogeneous Poisson process(HPP) and non-homogeneous Poisson (NHPP) process to develop the failure statistic over time [4] [7]. The HPP considers a constant failure occurrence failure rate. The NHPP, which failure rate is non-constant, is important to model the behavior of repairable systems. There are several models to obtain the failure rate, the most commonly is a power law proves or Weibull process.

Other studies [8] consider the Markov process-based models to assess reliability. These studies are based on suppose the deterioration levels of operating systems considering a discrete time Markov. Considering the weather effect, it is proposed a combined Markov model for a wind farm. The authors conclude that the failure and repair rate are affected by wind regimes.

The work presented in this paper is focused on maximizing the annual energy generation and minimizing the maintenance cost. Monte Carlo simulation is used to generate random failures time to calculate the cost of corrective maintenance and the unavailability due to down time. The equipment downtime supose a loss of energy production and repair cost. A Nelder-Mead simplex algorithm is used to perform the optimization and obtain the optimum value of preventive maintenance interval.

2. Wind turbine description

Wind turbine is composed of several equipment disposed in a serial configuration. The tower and foundation represent the structure of the wind turbine. The rotor is composed by the hub, which connects the blades with the main shaft, the blades, which are designed to transmit the rotational energy to the gearbox and the pitch system which controls the aerodinamic power and breaking.The drive train, gearbox, generator, yaw and hidraulic system are placed inside the nacelle. The drive train consist of shafts and bearings between the hub, the gearbox and the generator. The gearbox transforms the rotational speed from low revolution per minute (rpm) to high rpm required by the generator that converts this mechanical energy into electrical energy. To produce the maximum energy possible, the yaw system controls the alignement between the tower and the rotor and its function is to control the power output by measuring wind direction and setting the yaw and pitch system using a main computer inside the nacelle. The power generated by a wind turbine depends on its design, basically on the hub height and swept area.

Maintenance activities of wind turbines can be constrained by stochastic weather conditions, for example, when the wind velocity is around 20 m/s task is allowed perform maintenance. Nowadays, preventive maintenance is performed twice a year on each wind turbine. In this plan, neither metheorological conditions nor degradation are, a priori, taken into consideration what could result at the end of the year in a loss of energy produced.

3. Mathematical models

3.1. Reliability model

In this paper, the reliability function is defined as:

$$P(T > t) \quad = \quad 1 - P(T \leq t) = 1 - F(t) \ , \tag{1}$$

being t the chronological time and $F(t)$ the cumulative distribution function of failure. In this paper, to obtain the reliability function a Weibull distribution to model the failure process has been considered. In addition, an imperfect maintenance model, the Proportional Age Set-back (PAS) [9], allows to introduce the maintenance effect on the equipment age.

The following assumptions are made: 1) Maintenance effect depends on its effectiveness which is represented by a parameter,ϵ, ranged in the interval $[0, 1]$ and 2) corrective maintenance is assumed to be minimal repair ($\epsilon = 0$).

In the PAS approach [9], each maintenance activity is assumed to shift the origin of time from which the age of the equipment is evaluated. So, the age of the equipment in the m-period after $m-1$-maintenance activity is given by:

$$w_m(t, \epsilon) \quad = \quad w^{+}_{m-1}(t - t_m) \quad t \geq t_{m-1} \ , \tag{2}$$

being, t the chronological time, t_{m-1} is the time in which the equipment undertakes the $m-1$-maintenance activity and w^+_{m-1} is the age of the equipment inmediately after the $m-1$-maintenance activitiy which can be evaluated as:

$$w^+_{m-1} = \sum_{k=0}^{m-1} \prod_{r=0}^{k} (1-\epsilon_{m-r})(t_{m-k} - t_{m-k-1}) \ , \tag{3}$$

It is possible to obtain an age-dependent reliability model in which the induced or conditional failure rate, in period m after the maintenance number $m-1$, is given by:

$$h_m(w) = h(w(t,\epsilon)) + h_0 \quad w \geq w^+_{m-1} \ , \tag{4}$$

where h_0 is the initial failure rate of the equipment. Considering the age of the equipment after the maintenance $m-1$, $w_m(t,\epsilon)$, given by Eqn.(2), and adopting a two parameter Weibull model for failure rate, the expression for the induced failure rate after the maintenance number $m-1$ can be written as

$$h_m(w) = \theta^\gamma \gamma [w_m(t,\epsilon)] + h_0 \quad w \geq w^+_{m-1}, \tag{5}$$

where γ is the shape factor and θ is the characteristic time which represents the time scale. Then, replacing the expression corresponding to $w(t,\epsilon)$ into Eqn.(5) the expression for the induced failure rate in period m can be formulated as:

$$h_m(t,\epsilon) = \theta^\gamma \gamma (\sum_{k=0}^{m-1} \prod_{r=0}^{k} (1-\epsilon_{m-r})(t_{m-k} - t_{m-k-1})) + h_0, \tag{6}$$

The Reliability function $R_m(t)$ can be obtained from the following expression:

$$R_m(t) = \frac{\exp[-H_m(w)]}{\exp[-H^+_{m-1}(w)]} \tag{7}$$

substituting age by its expression in each maintenance model presented is obtained the reliability function as functions of time:

$$R_m(w) = \frac{\exp[-H_m(w(t,\epsilon))]}{\exp[-H^+_{m-1}(w(t,\epsilon)]} \tag{8}$$

where H_m, is the accumulated induced reliability function, can be formulated using the following equations:

$$H_m(w) = \int_0^w h_w(u)du \quad w \geq w^+_{m-1}, \tag{9}$$

Integrating the before equation can be obtained:

$$H_m(w) = [\theta w_m(t,\epsilon)]^\gamma + h_0 w_m(t,\epsilon) \ , \ w \geq w^+_{m-1}, \tag{10}$$

Then, can be assume $w(,\epsilon) = w^-_m$ in order to obtain H_{m-1}:

$$H^+_{m-1}(w) = H_{m-1}(w^+_{m-1}) = [\theta w^+_m]^\gamma + h_0 w^+ \ , \ w \geq w^+_{m-1}, \tag{11}$$

3.2. Wind velocity

Wind velocity is a stochastic variable that can be modeled using wind velocity measured data. There are several density functions to describe wind velocity behavior although the most common one is the Weibull distribution. The two parameters Weibull density function is given by:

$$f(v,\gamma,\theta) = \begin{cases} \gamma\theta(v\theta)^{\gamma-1}e^{-(t\theta)^{\gamma}} & v,\gamma,\theta > 0 \\ 0 & v \leq 0 \end{cases}, \tag{12}$$

where v is the wind velocity, γ is Weibull shape parameter and θ is the Weibull scale parameter.

3.3. Wind turbine curve. Power model

Basically, the power generated by a wind turbine depends on swept area and wind velocity. At very low wind velocity, the torque exerted by the wind on the turbine blades to make them rotate is insufficient. The speed at which the turbine starts to generate power is called the cut-in velocity, v_{ci},and it is typically between 3 and 4 m/s. There are one point on the risk of damage the rotor due to high velocity, this is called the cut-out velocity, v_{co}, and is usually around 25 m/s. At this moment the breaking system stops the wind turbine to prevent any damage. The wind velocity at which shut-down occurs is called the cut-out speed and its usually arround 20 m/s. So the power generated can be evaluated using:

$$P(v(t)) = \begin{cases} 0 & v < v_{ci} \ or \ v > v_{co}, \\ \frac{a}{1+b\exp(-cv(t))} & v_{ci} < v < v_r, \\ P_r & v_r < v < v_{co} \end{cases}, \tag{13}$$

where P_r is the rated power, the power generated when the wind velocity varies between rated velocity, v_r and v_{co}. The energy produced in a given period Δt can be evaluated as:

$$EP(\Delta t) = \Delta t P(v(\Delta t)), \tag{14}$$

where $P(v(\Delta t)$ is evaluated using Eqn.(13). In this paper has been considered the Annual Energy Produced (AEP) which can be calculated as:

$$AEP = \sum_{j=1}^{365}(\Delta t - \sigma_j - \mu_j)(P(v(\Delta t)_j), \tag{15}$$

where σ_j and μ_j are the corrective and preventive maintenance duration, respectively. The maximum annual energy produced AEP_{max} could be obtained when $\sigma = \mu = 0$.

3.4. Cost model

The occurrence of failures and breakdowns in the equipment of a wind turbine cause an increase in the operating costs and revenue loss. The design and implementation of an appropriate plan of preventive maintenance in a facility is one of the most interesting to try to optimize the efficiency of its operation. Preventive maintenance activities in wind turbines include testing, visual inspections, etc. and the corrective maintenance include task carried out in response to wear and tear of components, human errors and operational conditions such as over speeding, vibration, etc. The goal of the maintenance plan is to determine the best relationship between preventive and corrective maintenance to minimize the cost. In this case, the total cost model has been modeled using the cost contribution of performing scheduled maintenance (preventive maintenance) and unscheduled maintenance (corrective maintenance), using the following expressions:

$$c_{pm} = \sum_{i=1}^{n} \sigma_i c_{hpm}, \tag{16}$$

$$c_{cm} = \sum_{i=1}^{k} \mu_i c_{hcm}, \tag{17}$$

where, n is the preventive maintenance task performed to the interval time considered, c_{hpm} and c_{hcm} are the hourly personnel cost respectively and k is the number of failures observed in the same period. The total cost, c_t, has been evaluated as:

$$c_t = c_{pm} + c_{cm} \ , \tag{18}$$

4. Problem formulation

The models exposed in section 3 can be used to obtain the objective function in a multi-objective optimization problem to obtain the optimum maintenance plan.This Multiobjective Optimization Problem is transformed into a Single objective Optimization Problem (SOP)using the effectiveness concept:

$$y = f(x) = wE_p + (1 - w)(1 - E_c), \tag{19}$$

where w is the weighting coeficient with range interval $[0, 1]$ and E_p and E_c are the power and cost effictiveness, defined as:

$$E_p = \frac{AEP_{max} - AEP}{AEP_{max}}, \tag{20}$$

$$E_c = \frac{c_{pm}}{c_t} \ , \tag{21}$$

where AEP is calculated using Eqn. 15, c_{pm} and c_t are evaluated using Eqn. (16) (18), respectively.

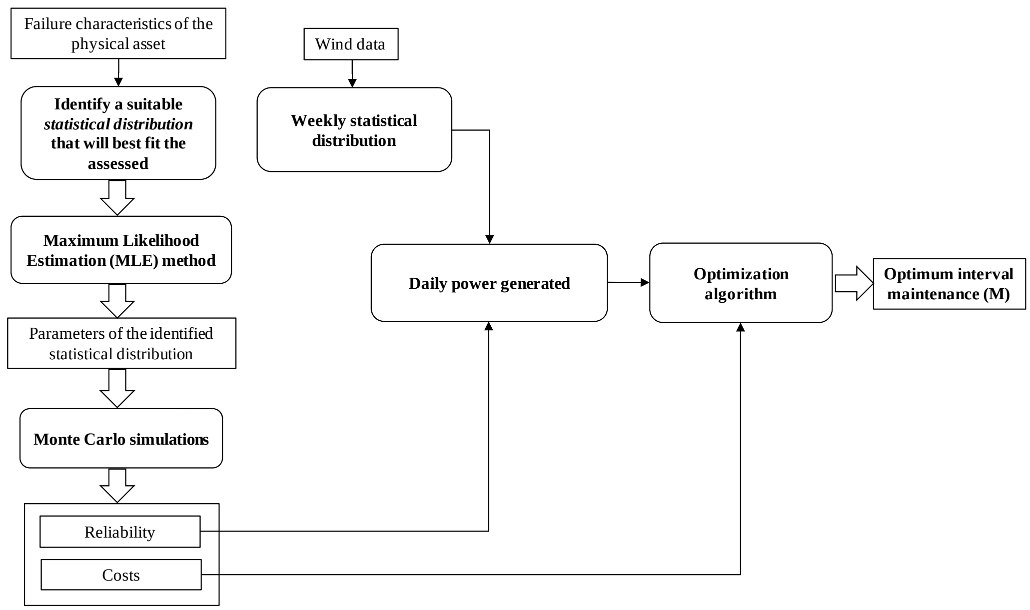

Figure 1: Problem formulation.

5. Methodology

The methodology proposed in this paper to find the best maintenance interval is presented in Fig.1. As shown in this figure, the optimization process is developed using the following procedure:

Step 1. The parameters associated to the reliability function are obtained using available wind turbine failure data. It is assumed (see section 3) that the failure process can be modeled using the two-parameter Weibull distribution. So, to characterize the reliability function the scale and shape parameters must be estimated. These parameters can be obtained using the Maximum Likelihood Estimation (MLE) method. For a given failure distribution model and a set of observed data, the likelihood function is given by:

$$L(\zeta, model, observeddata) = \prod h(t) \prod R(t) \ , \qquad (22)$$

where $h(t)$ is the failure rate and $R(t)$ the reliability function obtained from (6) and (7), respectively.

By maximizing the expression corresponding to $logL(x)$ the maximum likelihood estimators of the parameters are obtained. So, after the MLE process, the scale parameter,θ, and shape parameter ,γ, are obtained and the reliability function characterized.

In a similar way, the wind velocity distribution is obtained using hourly wind data measures and MLE method.

Step 2.According to Monte Carlo simulation, N random numbers are generated for the preventive and corrective maintenance duration, the failure times and wind speed. Using the analytical models presented in section 3 the Energy and Cost are evaluated for every trial. The procedure to obtain energy and cost values is the following:

a) Suppose that the wind turbine is operating in t=0.

b) Simulate the first failure time (TTF). Using the reliability function obtained in step 1 it is possible generate the first random failure using the inverse transformation method. The inverse transformation method provides the most direct way for generating a random sample from a distribution. In this method, the inverse of the probability density function is used and a random number between 0 and 1 is converted to a random value for the input distribution, thus is, for the failure times . The process can be described as follows:

Generate $U = Uniform[0, 1]$

Return $TTF = F^{-1}(U)$

being $F^{-1}(U)$ the inverse of the cumulative distribution function F which is given by in Eqn.(23). The duration associated with the failure generated is modeled using an uniform distribution.

$$F = (-log(U))^{\frac{1}{\theta}}\gamma \ , \tag{23}$$

c) Repeat step b) in a specific time span (in this case one year).

d) For each instant of time span the daily wind velocity is simulated using a Weibull distribution and a chronological daily energy and cost is obtained.

Step 3.The optimization is performed using direct search algorithm based on the Nelder Mead Simplex (NMS) method. When objective function has n decision variables, the NMS algorithm begins from n+1 initial values for these variables which define a simplex in the objective space.In each step, the method calculates a minimum for the objective function by performing concurrent searches following multiple directions, determined by vertex of current simplex, until a termination criterion is verified. So, the objective function is evaluated at extreme points of the simplex.

6. Case of application

The case of application is focused on optimizing the maintenance plan of wind turbine of 2MW. A generic failure database has been used. This data base contains information about, failure date, failure description and duration of corrective and preventive maintenance. Nowadays in a typical maintenance plan, the frequency of preventive maintenance is 6 months. Daily wind velocity data have been obtained from a spanish database to determine the wind behaviour.

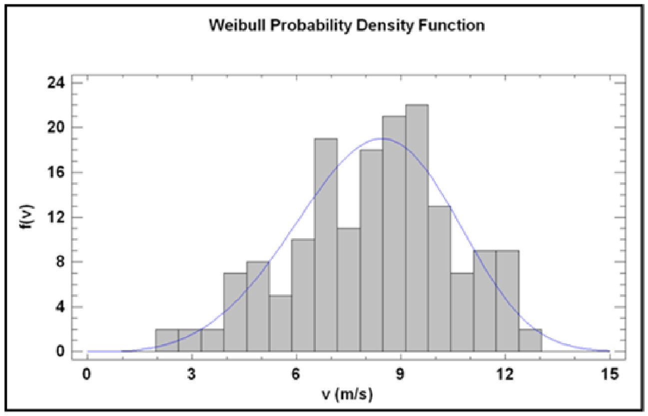

Figure 2: Probability density function of one week.

The behaviour of the two stochastics variables, the failure time and wind velocity, considered in this study have been modeled using Weibull distribution. Daily Wind data have been fitted for each week, as example of one week probability density function of wind velocity data as shown in Fig.2, in which fit the two paramenters (scale and shape) of the distribution are 9,03 m/s and 4,15, respectively. The time between failures of a wind turbine are used to performing the fit of failure data to Weibull distribution. The results of this fit as shown in Fig.3, where the shape parameter and the scale parameter are 839,26 $hours$ and 1,09, respectively.

Other stochastic variables considered in the study are the duration and the effectiveness of the maintenance tasks. The preventive maintenance duration is also modeled as a uniform distribution in the range of 6 and 10 hours and the corrective maintenance duration is also a uniform distribution between 10 and 20 hours and finally the maintenance effectiveness is considered to be a uniform distribution in the range of interval $[0,7;1]$. Monte Carlo simulation with 500 sampling has been used to generate random values of power, wind and failures. Optimization has been realized using a direct search algorithm, in this study in particular the Nelder-Mead simplex algorithm implemented in MatLab. [10], using Eqn. (19) as objective function, and the equations presented in section 2 to quantify the annual energy produced and cost criteria. The optimum maintenance interval obtained from optimization process is equal to 113 days.

Fig.4. shows the evolution of daily energy produced obtained from the optimization process. In this figure, a comparation between the behaviour of the AEP_{max} and the AEP is showed. Finally, the reliability evolution for a Monte Carlo simulation using the optimum preventive maintenance interval is presented in Fig.5. In Fig.5., can be observed the downtime due to preventive and corrective activities and the preventive maintenance effect on the reliability

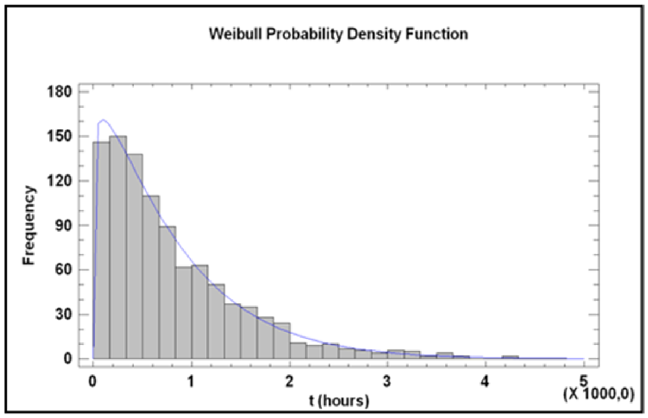

Figure 3: Probability density function of failure data.

function.

7. Conclusions

In the last years,the utilitation of wind energy has been increased consequently is need consider the reliability of energy produced that can be obtained and the associated costs. The proposed model in this paper can be used to find the optimum maintenance preventive strategy that minimize the annual power and minimize the cost taking into account the stochastic behaviour of wind velocity, reliability, maintenance duration and effectiveness.This study considers each wind turbine isolated, but preventive maintenance should be analyzed considering the whole wind farm.

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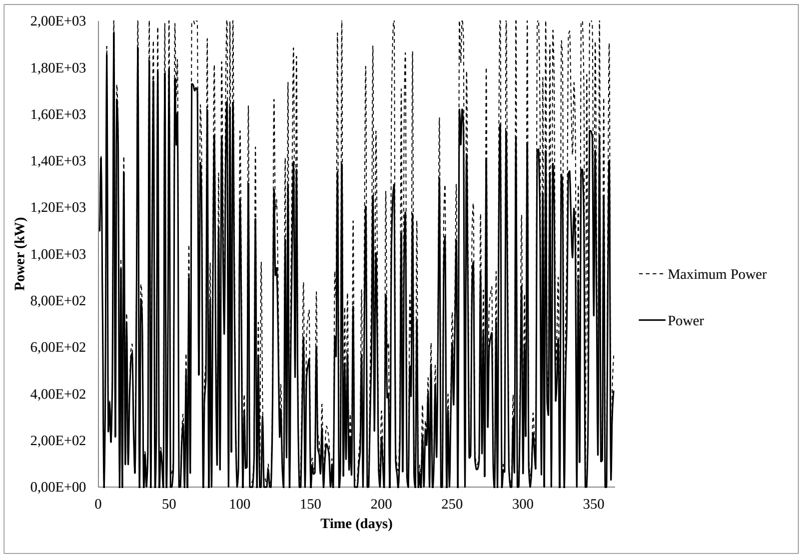

Figure 4: Annual energy produced.

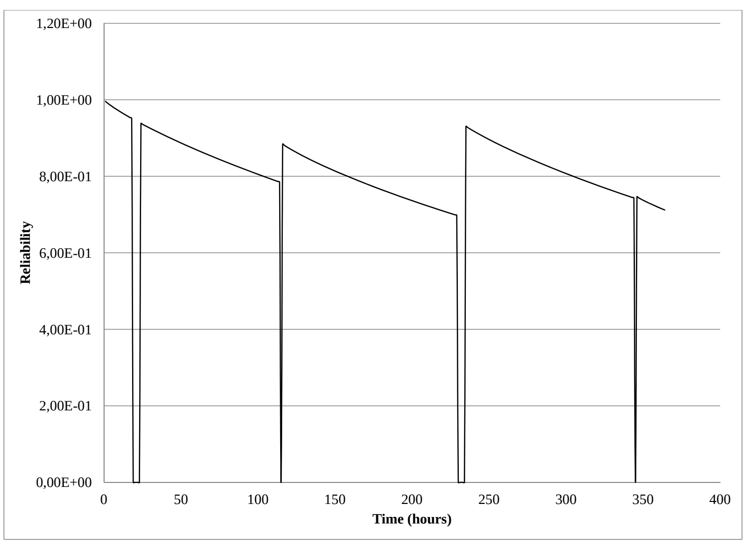

Figure 5: Reliability.

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