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Assessment of the wake effect on the energy production of onshore wind farms using GIS

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HIGHLIGHTS

- Annual energy production of onshore four wind farm estimated with GIS.
- Wake effect, roughness factor and elevation difference of WTs modeled and integrated into GIS.
- Wake effect impact represented with reduced efficiency coefficient (REC).
- Mean annual energy production and capacity factor underestimated of 3.56% and 1.11%.
- Mean REC of wind farm comprised between −0.087 and −0.2.

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ABSTRACT

In this study, we propose a method to estimate the mean annual energy production of a wind farm with a Geographic Information System (GIS). GIS allows for spatial modeling in many fields and has recently been applied in the field of renewable energy. The geographic features of a wind park are represented using spatial data such as topography, land cover, and wind resource. Wind resource layers contain data of the 16 wind directions, in which the wind rose is divided, including the frequency of the wind direction, the mean annual wind speed and the annual Weibull parameters k and C) estimated at 50 m height. The wind turbines are represented by points including information about the roughness of the surrounding terrain. Roughness is calculated within a GIS process that models the variation of the land cover over the year around the wind turbine position. The mean annual energy production is calculated coupling the technical characteristics of the wind turbines models with the wind resource. In addition, the wake effect between wind turbines has been included. A parameter called "reduced efficiency coefficient" has been introduced to assess the impact of the layout of wind farm on the annual energy production in respect to the change of the wind direction. The reduced efficiency coefficient shows that relatively regular wind farm layouts designed for exploiting the wind speed blowing from the prevailing wind direction can cause significant energy losses. In particular, when the wind comes from directions perpendicular to the prevailing one, the wind turbines waste up to 60% of the available energy. The method has been tested, comparing the actual annual energy production of four wind farms in Kansas (U.S.) with the estimated mean annual energy production. The validation demonstrated an average underestimation of 3.56% of the annual energy production and an average underestimation of 1.11% of the capacity factor. The results are encouraging and the developed process enables the quantification of the annual energy production with low uncertainties.

1. Introduction

With the depletion of conventional sources and the increase of global warming, RES have attracted the interest and a more and more significant mass of investments. Among all RES, wind energy has had a growth of 27% in the last five years for a total installed capacity of 230 GW at the end of 2011 [1] with an overall turnover of 50 billion Euro [2].

In order to improve the reliability and thus reduce the uncertainties in investments in the wind energy industry, several efforts have been made in fields such as the improvement of WT efficiency, the development of methods to predict the wind resource and to estimate the wind AEP. With respect to the estimate of

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Nomenclature

Abbreviation

AEP	annual energy production
AGL	above ground level
ASL	above sea level
DEM	digital elevation model
GIS	Geographic Information System
GW	gigawatt
NREL	National Renewable Energy Laboratory
PPA	power purchase agreement
RES	renewable energy sources
RIX	ruggedness index
WT(s)	wind turbine(s)

Symbols

a	induction factor of a WT
α	constant characteristic of the wake expansion
A	area rotor
A_o	overlapping area between wake of the WT_i and WT_k rotor
A_w	area wake
β	constant characteristic of the wake expansion
C	Weibull Scale coefficient
C_p	power coefficient
C_t	thrust coefficient
CF	capacity factor
γ	availability factor
Δ	difference
ΔLD	distance between two WTs along the wind direction
ΔHD	distance between two WTs perpendicular to the wind direction
Δz	difference of the elevation of two WTs rotors
D	rotor diameter (m)
DW	distance between the center of the WT rotor and the wake
ε	electrical and mechanical losses
φ	angle of the wind direction with respect to the reference
H	hub height (m)
H_{ref}	reference height at which the wind speed is known (m)
K	Weibull Shape factor at the hub height
λ	ratio of the distance x_i between two WTs to the D
μ	frequency
n	number of sectors of the wind rose
n_{30}	number of raster cells in a given area with a slope larger than 30%
n_{all}	total number of raster cells in the area
P	power output of a WT
r	radius
REC	reduced efficiency coefficient
RIX_{wt}	RIX value at the wind turbine location
RIX_m	RIX value at the measurement station
φ	wind direction
U	wind speed
$u_{cut\text{-}in}$	wind speed at which a WT starts producing electricity
$u_{cut\text{-}off}$	wind speed at which a WT stops producing electricity
$\bar{u}_H$	wind speed at the hub height (m/s)
$\bar{u}_{ref}$	wind speed at the reference height (m/s)
$\bar{u}_i$	undisturbed inlet wind speed velocity
$\bar{u}_k$	inlet wind speed at the WT in downstream
$\bar{u}_{ik}$	velocity of the wake approaching the WT_k
u_{rated}	wind speed at which a WT reaches the maximum power output
z	WT rotor elevation
z_0	terrain roughness

Subscript

a	at the hub height
Actual	actual AEP
Avail	availability
Cut-in	cut-in wind speed of a WT
Cut-off	cut-off wind speed of a WT
Ref	reference height at which the wind data are known
i	i-WT in upstream
j	number of WT of a wind energy project
loss	losses
k	k-WT in downstream
m	measurement location
predicted	predicted AEP
rated	rated wind speed
ww	with wake included
w/w	without wake
WT	wind turbine

the energy production, different models have been developed both for short-term and long-term assessments using statistical and physical approaches.

In this research a method for predicting the AEP of wind farms using a GIS platform has been developed using a physical approach.

A review of previous work is presented in Section 2; in Section 3 the discussion continues with the methodology applied in this process and the characteristics of the data used. Section 4 describes the workflow and in Section 5, the case studies and conclusions are presented.

2. Literature review

Both short-term and long-term energy production estimates are the most important factors that impact the performances, management and profitability of a wind energy project, therefore significant work has been done in the last decades in order to reduce their uncertainties and improve their reliability. The energy production depends on the wind speed prediction and the estimate of different losses due to the wake effect, mechanical performances of the equipment etc. The wind speed profile is influenced by multiple local obstacles such as topography and land cover and usually varies with height. In addition, the interaction between WTs generates losses and thus further uncertainties in estimating the energy generation. Existing models focus both on the estimate of the wind resource and the energy production of wind farms. The models to estimate the wind energy generation can be divided into two main groups: physical and statistical models. Previous work has widely analyzed and compared these two methods aimed to predict the short- and long-term wind power energy [3] with the scope of identifying which one performs best. The conclusion is that some models are good for short-term predictions while others are more reliable and accurate for long-term predictions. The study finally suggests to develop new technics that adopt more advanced mathematical-based approaches, to combine different physical and statistical models for both in long- and short-term prediction and, finally, to test them on practical applications. A similar study has been carried out to create a benchmark of different models and assessing the uncertainty of the short-term predictions [4]. In other research studies high resolution regional atmospheric systems