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Statistical learning approach for wind resource assessment

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ABSTRACT

Wind resource assessment is fundamental when selecting a site for wind energy projects. Wind is influenced by several environmental factors and understanding its spatial variability is key in determining the economic viability of a site. Numerical wind flow models, which solve physical equations that govern air flows, are the industry standard for wind resource assessment. These methods have been proven over the years to be able to estimate the wind resource with a relatively high accuracy. However, measuring stations, which provide the starting data for every wind estimation, are often located at some distance from each other, in some cases tens of kilometres or more. This adds an unavoidable amount of uncertainty to the estimations, which can be difficult and time consuming to calculate with numerical wind flow models. For this reason, even though there are ways of computing the overall error of the estimations, methods based on physics fail to provide planners with detailed spatial representations of the uncertainty pattern. In this paper we introduce a statistical method for estimating the wind resource, based on statistical learning. In particular, we present an approach based on ensembles of regression trees, to estimate the wind speed and direction distributions continuously over the United Kingdom (UK), and provide planners with a detailed account of the spatial pattern of the wind map uncertainty.
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Contents

1. Introduction

Wind energy plays a key role in reducing the level of CO_2 emissions required to mitigate the worst effects of climate change. By 2020 the UK has pledged to produce 30% of its electricity from

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renewable sources [1], compared to 17.8% today [2]. With the depletion of conventional sources and the increase of global warming Renewable Energy Sources (RES) have attracted the interest of investors. Among all RES, wind energy has had a substantial growth over the last five years, reaching a global installed capacity of around 370 GW (gigawatts) at the end of 2014 with an overall turnover of 277 billion Euros [3]. Moreover, according to the latest statistics [4], electricity produced from onshore wind farms is becoming cheaper than other traditional sources of electricity such as nuclear, coal, and combined gas cycle. In the United States the unsubsidized levelized cost of 1 MWh (megawatthour) produced by onshore wind is already lower or equal to all other sources of electricity.

When selecting a site for investing in a wind energy project, wind resource assessment plays a fundamental role. Meteorological stations collect climate data, but they are sparsely located and therefore do not provide the full data coverage necessary for the optimal placement of wind farms. In order to obtain an estimate of the wind characteristics in unknown locations, a way to model the wind field is required. In the last decades, multiple models have been developed for this scope and the research in the field has focused on two main directions: numerical wind flow models (i.e. methods based on physics, also referred to as physical methods) and statistical methods. Physical methods model the wind field by solving physical equation, such as the equations that govern the mass and momentum-conservation laws, or computational-fluids dynamic models. Statistical methods on the contrary, estimate the wind resource by correlating past observations with environmental data, such as elevation, slope, and temperature. Both methods have been widely used in literature, at various scales and with different level of accuracy. Below we present an extensive overview of the literature to provide the reader with a classification of wind resource assessment methods.

1.1. *Numerical wind flow models*

These methods estimate the wind resource by solving some of the equations that govern the motion of air in the atmosphere. Numerical wind flow models can be divided by level of sophistication or complexity [5] and partly also according to the scale at which they operate. In wind resource assessment we generally refer to three main scales of operation: macro-scale (known as synoptic scale with a resolution in the order of 2000 km or larger), meso-scale (few kilometres to thousands kilometres) and micro-scale (hundreds of meters to few kilometres). Synoptic scale models study large-scale phenomena, such as large depression fronts, which are mostly driven by Coriolis force and pressure gradient. These methods will not be treated in this review.

The first level of sophistication is occupied by mass-consistent models, such as NOABL (Numerical Objective Analysis Boundary Layer), developed in the ‘70 s in the US [6,7]. These methods solve only the equation of conservation of mass, which when applied to the atmosphere states that if a wind mass is forced over a slope it must accelerate so that the same volume of air passes in any given region [5]. Mass-consistent methods are still widely used for generating both meso-scale and micro-scale wind speed maps. Of particular interest is the work carried out in the UK by the UK Energy Technology Support Unit (ETSU) for the creation of a long-term wind speed database [8]. They started from overlapping grids of 100 km of resolution, with data collected from 56 stations for a time period of 10 years, from 1975 to 1984. They then applied NOABL to downscale the map at 1 km of resolution at three heights: 10 m, 25 m and 45 m. To the best of our knowledge nowhere in literature there is a mention of the computational time needed to create the wind map mentioned above. However, since these long-term databases are updated very infrequently, the time needed to create them is somewhat not influential in the planning process for new wind farms. For micro-scaling these data would be used as look-up tables and their estimates would just be further downscaled, thus minimizing computational time. Regarding its accuracy, the technical report from Best et al. [9], created for the MET Office (UK Meteorological Office), shows a plot of wind estimations against weather observations from which the overall deviation of the estimates seems to be around 2–5 m/s. Moreover, another report from the MET Office [10] mentioned the bias of the estimates (i.e. the mean of the residuals' distribution) from this method as equal to 1 m/s.

The second level of sophistication is occupied by models, developed in the ‘80 s and ‘90 s, to include not only mass-conservation, but also momentum-conservation. These models are based on the theory advanced by Jackson and Hunt [11] and work by solving a linearized form of the Navier-Stokes equation governing fluid flows. Because of this characteristic these models are often referred to as linear wind flow models. Probably the most famous linear model is WaSP (Wind Atlas Analysis and Application Program [12]), developed by Risoe National Laboratory of Denmark and used to create the European Wind Atlas in 1989 [13]. The Jackson-Hunt theory assumes that topography causes small perturbations in an otherwise constant wind flow, this allows the equations to be solved efficiently [5]. WaSP incorporates techniques to account for obstacles and roughness changes, even though it is not equipped to handle complex terrains [5]. Despite its known limitations, WaSP has been and remains very popular in the industry and has been used to generate various wind speed maps globally [14–17]. Regarding the scale of analysis, WaSP can be used for both meso- and micro-scale modelling. In the late ‘90 s for example, it was coupled with the Karlsruhe Atmospheric Mesoscale Model (KAMM) [18], to account for topography and create the first example of meso-micro scale model of the wind resource [19].

In alternative to linear models, the next level of sophistication consists of methods able to solve the full spectrum of equations of computational fluid dynamics (CFD) applied to air flows. These models take into account mass and momentum conservation, plus the effect of turbulence created by the interaction between wind and complex terrains. Examples of these model are based on Reynolds Average Navier Stokes (RANS) turbulence models [20, 21], and the Large-Eddy-Simulation (LES) model [22–25]. Additional information are provided in the comprehensive review of these models applied to fine-scale computation of wind flows carried out by Ayotte [26].

The final level of sophistication is occupied by Mesoscale Numerical Weather Prediction (NWP) Models [5]. These methods have been developed for weather forecasting; they include the full sets CFD equations, but they also include schemes to take into account: solar and infrared radiations, a soil model, clouds microphysics and convection. Examples of such models are: the Regional Atmospheric Modeling System (RAMS, http://rams.atmos.colostate.edu/rams-description.html), Skiron (http://forecast.uoa.gr/index.php), Weather Research and Forecasting (WRF, http://www.wrf-model.org/index.php), MM5 (http://www2.mmm.ucar.edu/mm5/overview.html), Consortium for Small scale Modeling COSMO (http://cosmo-model.cscs.ch/). These methods were developed to forecast weather patterns, based on the current situation. They are applied at the local and global scale, starting from direct weather observations from stations, radiosondes or satellite data. Due to enormous amount of equations to solve simultaneously these methods require substantial amount of computational resources to be used successfully, and cannot be used for micro-scale modelling with the current generation of supercomputers. For this reason, numerical approximations is often applied. NWP divide the atmosphere in 3D volumes

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