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Correlation between wind power generation in the European countries

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A R T I C L E I N F O

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The correlations between wind power generation in different countries are important for quantifying the reductions in variability when electrically interconnecting the countries. Hourly, country-wise time series of wind power output were generated for all European countries using MERRA reanalysis data. By comparing the model output with actual measurements, it is shown that this approach is appropriate for studying correlations. In order to deepen the analysis, correlation coefficients were not only computed for these time series, but also for the one hour step changes and for band-pass filtered data. The general pattern is that correlations reduce with separation distance in an exponential fashion and are highest for the long-term components ($T > 4$ months) and lowest for step changes and short-term components ($T < 2$ days). Interesting deviations from this pattern however exist. When comparing to earlier results for individual farms, the exponential decay is slower, in particular for step changes.

1. Introduction

The electric output from wind farms varies over a wide range of time scales, from sub-second fluctuations to variations over decades. The intermittency in the net load (*Load* – *Wind* – *Photovoltaics*) has to be balanced by other energy sources such as hydro power and gas turbines. Different time scales of wind power variability pose different challenges for the power system. For large offshore farms, the variations from minute to minute can be substantial and require flexibility in the (local) grid [1]. A lot of attention has been focused on the slightly longer variations on a time-scale of around one and up to a few hours, which can pose a significant challenge [2]. In particular, the step changes in aggregated output from hour to hour are commonly analysed in variability and integration studies [3–5]. Seasonal variations on the other hand requires large reservoirs if hydro power is the primary source for balancing.

The focus on variability in the 1–6 h time scale is not surprising since many power systems to a large degree rely on thermal generation for balancing wind power fluctuations. These plants generally require a few hours to ramp up their generation to the desired output. For hydro dominated systems (e.g. the Nordic system), it is however not obvious that this time scale of wind power variability is the most difficult to handle. Discussions with the Swedish power company Vattenfall, a major hydro power operator, actually suggest that variability on the synoptic time scale (a few days) could be more problematic to manage if wind power capacity was to be significantly increased. The reasons for this are primarily increased net load forecast errors and environmental regulations in how the hydro power plants are allowed to be operated.

Many possible paths are available to alleviate the problems related to the intermittency of wind power, including e.g. energy storage and demand side response. Another option is to reduce the variability itself by interconnecting countries or regions [6]. The linear correlation between wind power generation in different regions gives us information on the advantage of increasing transmission capacity between power systems in order to reduce the combined variability. Regions with a low or even negative correlation benefit most from being more tightly interconnected.

The aim of this paper is to quantify the correlations between wind power generation in different countries in Europe. To our knowledge, it is the first time that this type of analysis is performed in such a systematic way, i.e. not only for a handful of countries or regions. We also want to examine whether the exponential model for correlation versus separation distance commonly used for farm output (see Section 2.1) is appropriate also for country-wise

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generation. To get a more complete picture, correlation coefficients were studied for hourly data and one hour step changes as well as for filtered data. The filtering, described in Section 2.4, is useful since it allows us to isolate and study particular frequency bands, e.g. the synoptic time scale. Since sufficiently long wind power time series were not available for many countries, the generation was modelled from meteorological reanalysis data. In order to gain confidence for this methodology, the model output was first compared to measurements from three different countries. For the final analysis, the anticipated fleet of wind turbines (WTs) as of year 2020 and modelled time series spanning from 2005 to 2012 (eight years) were used. Throughout the paper, Pearson's linear correlations are considered. The differences compared to Spearman's rank correlations are however generally within a few percentage points.

This paper is structured as follows: Section 2 gives a theoretical background and describes the methods used. Section 3 begins with a comparison of the output from the model with actual historical generation. Subsequently the results in form of correlation coefficients are given. The paper concludes with a discussion and conclusions in Sections 4–5. Additional figures and tables as well as a Matlab file with hourly generation for each country are provided as supplementary material.

2. Theory and methods

2.1. Benefits of interconnection

By combining wind power output from several countries, the variance can be lower than for a similar installed capacity in only one country. Let us consider the weighted combination of wind power from N countries:

$$P_{tot} = \sum_{i=1}^{N} w_i P_i, \tag{1}$$

where w_i is the weight and P_i is the generation time series for country i. The variance of P_{tot} can be computed as

$$Var(P_{tot}) = \sum_{i=1}^{N} \sum_{j=1}^{N} w_i w_j \sigma_i \sigma_j \rho_{ij}, \tag{2}$$

where σ_x is the standard deviation for the generation in country x and ρ_{ij} is the correlation between generation in countries i and j. The importance of ρ is obvious from the equation. Consider for instance the combination of two equally weighted ($w = 0.5$) time series with unity standard deviations. With ρ of -1, 0 and 1, the variance of the combined outputs become 0, 0.5 and 1 respectively. In other words, as long as $\rho < 1$, interconnection is beneficial in terms of lowering the combined variability.

It is well known that the outputs from wind farms are correlated and that, in general, ρ decreases with longer separation distances [7]. A commonly used correlation model is given by

$$\rho(d) = \alpha \cdot e^{-d/D}, \tag{3}$$

where d is the distance between the farms and D is a parameter determining how fast ρ decreases with distance. The separation distances were calculated between the mass centres of the installed wind power capacity for each country using the Haversine formula [8]. The α parameter is sometimes fixed to unity and sometimes allowed to take other values as well. A review of models and corresponding parameter values can be found in Martin et al. [7]. Almost all of the works cited therein present models for correlation between output of individual farms or wind speed measurements. The same analysis can however be performed with nationally or regionally aggregated wind power time series [5,9]. It can also be noted that the correlation of wind power forecast errors has a similar dependence on distance [10,11], although ρ here decays considerably faster.

2.2. Study area

Several of the countries in Europe are very small and/or have negligible installed wind power capacity. In order to give a clearer presentation of the results, a few very small states were omitted from the analysis and some of the countries were grouped together, see the bulleted list below and Fig. 1. For the remainder of this paper, when referring to a “country”, it could be an actual country or a region in the bulleted list.

- Austria and Switzerland (SZ)
- The Baltic States (Estonia, Latvia and Lithuania)
- Benelux (Belgium, the Netherlands and Luxembourg)
- Czech Republic and Slovakia (LO)
- Greece and (the whole of) Cyprus (CY)
- Western Balkans (Bosnia & Herzegovina, Macedonia, Serbia, Croatia, Montenegro and Albania) and Slovenia (SI)
- Romania and Moldova (MD)

2.3. Model of hourly generation

In an earlier work [12], the MERRA reanalysis dataset [13] was used for modelling hourly, aggregated wind power generation. A reanalysis uses an unchanging atmospheric model and analysis system to produce a gridded and complete dataset of relatively consistent quality (unlike operational models which improve over time). MERRA, the Modern Era Retrospective-Analysis for Research and Applications, is produced by NASA and covers the period 1979–2016. For wind speed, temperature, air pressure and other relevant variables, the temporal and spatial resolutions are one hour and $1/2^\circ \times 2/3^\circ$ respectively. The method in Ref. [12] proved to be successful; when validating with data from the Swedish transmission system operator (TSO), the root mean square error (RMSE) was 3.8% and the correlation coefficient was 0.98. The five basic steps of the method are:

1. Start with MERRA time series and information on each WT.
2. Calculate the hourly wind vector at turbine hub height.
3. Calculate hourly generation for each WT, including losses of different kinds.
4. Aggregate hourly generation for the studied area.
5. Use bias corrections to improve the results.

The abovementioned model requires e.g. coordinates, installed capacity, rotor diameter and estimated annual energy yield for all individual WTs. In the present study, much less details were available on existing WTs for most of the countries and therefore a simplified approach was taken. Average capacity factors (CFs) for onshore farms as of 2020 were estimated for each country (see Section 2.5) and all offshore farms were assumed to have a capacity factor of 0.43. Ten year long time series were computed for each MERRA grid point using the same parameter settings as in Ref. [14] except that direction dependent losses were not considered and no seasonal/diurnal bias correction was performed. The time series were finally weighted by the assumed distribution of farms (see Section 2.5) to give country-wise, hourly generation.