Applied Energy 165 (2016) 735–747

Contents lists available at ScienceDirect

Applied Energy

journal homepage: www.elsevier.com/locate/apenergy

Exploiting sparsity of interconnections in spatio-temporal wind speed forecasting using Wavelet Transform

Akin Tascikaraoglu [a,b,*], Borhan M. Sanandaji [a], Kameshwar Poolla [a], Pravin Varaiya [a]

[a] Department of Electrical Engineering and Computer Sciences, University of California, Berkeley, CA, USA
[b] Department of Electrical Engineering, Yildiz Technical University, Istanbul, Turkey

HIGHLIGHTS

- We propose a spatio-temporal approach for wind speed forecasting.
- The method is based on a combination of Wavelet decomposition and structured-sparse recovery.
- Our analyses confirm that low-dimensional structures govern the interactions between stations.
- Our method particularly shows improvements for profiles with high ramps.
- We examine our approach on real data and illustrate its superiority over a set of benchmark models.

ARTICLE INFO

Article history:
Received 14 September 2015
Received in revised form 19 November 2015
Accepted 17 December 2015

Keywords:
Wind forecasting
Compressive sensing
Spatial correlation
Wavelet Transform

ABSTRACT

Integration of renewable energy resources into the power grid is essential in achieving the envisioned sustainable energy future. Stochasticity and intermittency characteristics of renewable energies, however, present challenges for integrating these resources into the existing grid in a large scale. Reliable renewable energy integration is facilitated by accurate wind forecasts. In this paper, we propose a novel wind speed forecasting method which first utilizes Wavelet Transform (WT) for decomposition of the wind speed data into more stationary components and then uses a *spatio-temporal* model on each sub-series for incorporating both temporal and spatial information. The proposed spatio-temporal forecasting approach on each sub-series is based on the assumption that there usually exists an intrinsic low-dimensional structure between time series data in a collection of meteorological stations. Our approach is inspired by Compressive Sensing (CS) and structured-sparse recovery algorithms. Based on detailed case studies, we show that the proposed approach based on exploiting the sparsity of correlations between a large set of meteorological stations and decomposing time series for higher-accuracy forecasts considerably improve the short-term forecasts compared to the temporal and spatio-temporal benchmark methods.

1. Introduction

1.1. Variable energy resources

Environmental and geopolitical concerns associated with the current power grid have motivated many countries and many states in United States to setup aggressive Renewable Portfolio Standard (RPS). Volatility, stochasticity, and intermittency characteristics of renewable energies, however, present challenges for integrating these resources into the existing grid in a large scale as the proper functioning of an electric grid requires a continuous power balance between supply and demand [1,2]. While ancillary services such as load following and frequency regulation have been proposed to compensate for such mismatches [3,4], obtaining more precise and reliable forecasts remains as a crucial step towards renewable energy integration [5].

1.2. Wind speed forecasting methods

Among different renewable energy resources, wind energy is one of the most attractive energies and its development has been radically increased around the world. According to a report, total wind power capacity in the world has doubled every three years since 2000 and reached an installed capacity of 197 GW in 2010

* Corresponding author at: Department of Electrical Engineering, Yildiz Technical University, Istanbul, Turkey. Tel.: +90 212 3835866; fax: +90 212 3835858.
E-mail addresses: atasci@berkeley.edu, atasci@yildiz.edu.tr (A. Tascikaraoglu).

http://dx.doi.org/10.1016/j.apenergy.2015.12.082
0306-2619/

and 369 GW in 2014 [6]. Wind power can be forecasted directly; however, forecasting wind speed and then converting the speed forecasts to power forecasts using commercially available wind turbine power curves is generally considered as a better approach [7]. This approach is more effective as, for example, wind turbines with different ratings in a wind farm might experience the same wind speed but have different wind power [8]. Therefore, we focus on wind speed forecasting in this paper.

Wind speed forecasting approaches can be classified to various categories: (i) shorter-term forecasting vs. longer-term forecasting, (ii) data-driven methods vs. model-based methods, and (iii) point forecasting vs. probabilistic forecasting. There are advantages and disadvantages associated with each approach. For instance, data-driven models are widely considered to be the most competitive methods for higher temporal resolutions due to the slightly changing wind speeds during these periods [9]. Recently, the main interest has turned from individual models to advanced combination models, which leverage the unique advantages of combining several single models in order to mitigate the prediction errors [10,11]. Also much effort has been devoted at the last few years to the wind speed forecasting methods accounting for the data collected from both the site of interest and other points (wind farms and meteorological stations) on its surrounding region over a reasonable period of time. In order to utilize both two state-of-art approaches, we aim to perform short-term point forecasting based on a two-stage model that combines a data preprocessing method, namely Wavelet Transform (WT), and a *spatio-temporal* model in this paper.

1.3. WT-based spatio-temporal wind speed forecasting

The main objective of data preprocessing models is to realize a preliminary process on data sets by decomposing the nonlinear time series into more stationary sub-series which are generally easier to analyze. Among various techniques, WT-based methods can be pointed out as the prevailing approach in wind forecasting due to its easy implementation and adaptive ability of time–frequency analysis [10]. The benefits of WT on the prediction performance have been proven for forecasting approaches using both linear and nonlinear models. Catalão et al. [12] present an approach which combines WT and Neural Network (NN) for short-term wind power forecasting. Several approaches are studied for wind speed forecasting which utilize WT, wavelet packet decomposition and Artificial Neural Network (ANN) [13]. Support Vector Machines (SVM), which is closely related to ANN in terms of its structure, is also used in combination with WT [14]. Liu et al. [15] also propose a model based on WT and SVM, in which the parameters of SVM are optimized using Genetic Algorithm (GA). A hybrid model consists of two-layer WT and Artificial Bee Colony (ABC) algorithm-based Relevance Vector Machine (RVM), which has a sparser representation compared to SVM, is also presented for speed forecasts [16]. In [17], WT is utilized in combination with a Feed Forward Neural Network (FFNN) model for wind power predictions with the objective of increasing the efficiency in a stand-alone system.

In this study, we first apply WT for decomposing the wind speed data into some sub-series. We then apply our proposed *spatio-temporal* wind speed forecasting method on each sub-series. We show that the overall procedure improves the prediction performance. Spatio-temporal forecasting approaches combine spatial information from different locations in a geographical area to get higher-accuracy predictions compared with predictions generated only using local data. The underlying assumption is that a considerable correlation exists between data of target meteorological station and data from the stations in its vicinity. It is expected that these correlations also appear in the wind forecasts, possibly with some time lags depending primarily on the wind speed and distance between the sites. The potential benefits of these models and the analysis of the contribution of each input candidate on the system performance have been investigated in a number of studies. Alexiadis et al. [18] present an ANN-based spatio-temporal technique for wind speed and power forecasts up to several hours ahead. A fuzzy model using data from various stations in and around a wind farm is put forward by Damousis et al. [19] in order to benefit from autocorrelation and cross-correlation between a set of wind speed data. Gneiting et al. [20] introduce a wind speed prediction method, namely the Regime Switching Space–Time Diurnal (RSTD) model, which is based on spatial and temporal information. This approach is enhanced by Hering and Genton [21] in the Trigonometric Direction Diurnal (TDD) model, incorporating wind direction in the model. Tastu et al. [22] present different data-driven models (such as Autoregressive (AR)-based models) in order to investigate the relation between various variables and the corresponding forecast error. Similarly, multivariate AR models are used to exploit geographically dispersed wind data by Hill et al. [23]. Xie et al. [24] propose a probabilistic forecast model based on TDD model including spatial as well as the temporal correlations and geostrophic wind information. Dowell et al. [25] present an adaptive filter for wind speed and direction forecasting on the basis of spatial correlations at neighbor areas. A method with probabilistic wind generation power forecasts is developed in [26] taking the spatial information into account. Wind farm generation forecast is studied in another work [27] by applying spatio-temporal analysis to data from multiple classes of wind turbines, in which finite-state Markov chain models are obtained for short-term forecasts.

1.4. Our contribution

We propose a novel spatio-temporal approach for wind speed forecasting. Our contributions are as follows. We first show that there exist low-dimensional structures governing the interactions among a set of meteorological stations, and exploiting such structures significantly enhances forecasting performance. We formulate the forecasting task as a linear inverse problem. We then use tools from structured-sparse recovery to find a *block-sparse* solution. The proposed approach dynamically determines the wind speed data set to be used in the forecast of the target station for the following prediction horizon. In other words, the proposed algorithm determines the contribution of each meteorological station on the next forecast by assigning them coefficients proportional to their similarities with the recent data of the target station. Contrary to the widely-used conventional time series methods considering predefined structures in which the order of each meteorological station is determined once and then kept constant during all of the prediction periods, the proposed adaptive algorithm provides an up-to-date input set for each prediction horizon without realizing the time-consuming order selection process. Thus, the model structure of the proposed algorithm helps improve the prediction accuracy, especially for longer prediction times including daily, seasonal, and annual cycles in weather conditions.

Second, we show that combining the WT with the proposed spatio-temporal method further improves the forecasting accuracy, particularly for wind profiles with high up and down ramps. Furthermore, the indicated improvements are accomplished using a smaller training data set for the proposed algorithm while usually larger data sets are included in other benchmark methods considered in this paper for obtaining reasonable results. Lastly, our analysis shows that the proposed method results in highly concentrated prediction error values which further facilitate the applicability of the forecasts in energy market commitment and dispatch.