Renewable Energy 93 (2016) 38–44

Contents lists available at ScienceDirect

Renewable Energy

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

Improved week-ahead predictions of wind speed using simple linear models with wavelet decomposition

Dennis C. Kiplangat [a, b], K. Asokan [c], K. Satheesh Kumar [a, *]

[a] Department of Futures Studies, University of Kerala, Kariavattom, Kerala, 695 581, India
[b] Department of Statistics & Actuarial Science, Dedan Kimathi University of Technology, Nyeri, Kenya
[c] Department of Mathematics, College of Engineering, Thiruvananthapuram, Kerala, 695 016, India

ARTICLE INFO

Article history:
Received 6 May 2015
Received in revised form
4 February 2016
Accepted 18 February 2016
Available online 27 February 2016

Keywords:
Wind speed forecasting
Time series decomposition
Auto-regressive models
Fractional-ARIMA models

ABSTRACT

Simple linear methods are widely used for time series modelling and prediction and in particular for the forecast of wind speed variations. Linear prediction models are popular for their simplicity and computational efficiency, but their prediction accuracy generally deteriorates beyond a few time steps. In this paper we demonstrate that the prediction accuracy of simple auto-regressive (AR) models can be significantly improved, by as much as 60.15% for day-ahead predictions and up to 18.25% for week-ahead predictions, when combined with suitable time series decomposition. The comparison with new reference forecast model (NRFM) also shows similar accuracy gain of week ahead predictions. The combined model is capable of forecasting wind speed up to 7 days ahead with an average root mean square error less than 3 m/s. We also compare the performance of AR and f-ARIMA models in wind speed prediction and observe that the f-ARIMA model is no better than the AR model when used in combination with time series decomposition.

1. Introduction

Wind is widely recognized as one of the fastest growing alternate sources of energy all over the world. Wind energy is clean, economically viable and safe for the environment and is available in abundance. Compared to power produced from gas or coal, each MWh of wind power saves no less than 500 kgs of green house effect gases from being released into the atmosphere and this makes wind power one of the most eco-friendly sources of energy [1,2]. Over the last few years there has been a steady growth of the generation and use of wind power and as of 2013, the total installed capacity of wind power stands at 318 GW. According to European Wind Energy Association, if the growth of wind power generation continues at the current rate, it would account for more than 12% of the total energy demands by the year 2020 [3]. A major factor affecting wind power production is the highly fluctuating nature of wind speed, under the influence of numerous meteorological factors. These variations occur at all time scales ranging from seconds to months and even years and being able to predict these fluctuations is a key factor in the production and management of wind energy. Based on the length of the forecasting period, wind speed predictions are generally classified as short-term (up to 6 h ahead), medium term (6 h–1 day ahead) and long-term (1 day–1 week ahead) [4], and improving the accuracy of predictions at all these time-scales is crucial at various stages of wind energy production and management. Short term forecasts ranging from milliseconds to a few minutes are needed for active turbine control and managing wind energy at electricity grids [5,6] and forecasts in the range of a few hours up to a few days are useful in energy management and trading, especially in liberalized electricity markets where users devise best bidding strategy based on expected power production [7]. Long-term forecasts of up to several days ahead are useful in managing the maintenance of wind farms and transmission lines [8]. Methods for accurate prediction of wind speed has therefore emerged as an important research area in recent years.

Various models for wind prediction include physical models, which use complex mathematical equations to describe the physical relationship between various atmospheric parameters and local topography, statistical models which use time series of past data or probability distribution of wind speed for future predictions and also hybrid models which combine physical models with

* Corresponding author.
E-mail addresses: dennis.cheruiyot@dkut.ac.ke (D.C. Kiplangat), asokank@cet.ac.in (K. Asokan), kskumar@keralauniversity.ac (K.S. Kumar).

http://dx.doi.org/10.1016/j.renene.2016.02.054
0960-1481/

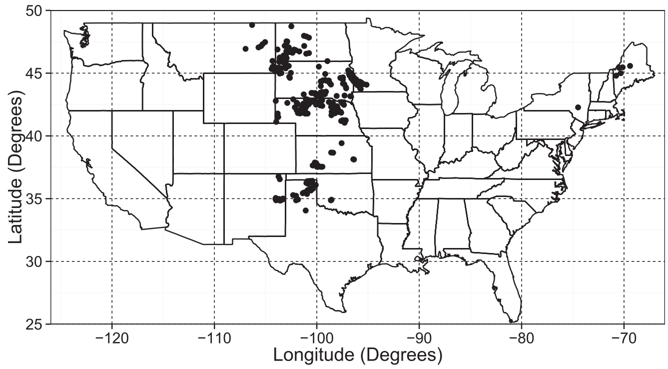

Fig. 1. The geographical locations, denoted by filled circles, for the 234 sites selected for wind speed data analysis and prediction.

statistical tools [9]. A thorough review of the current status of wind power forecast models, especially of the meteorology based approaches, can be found in Refs. [10] and [11]. Provided the meteorological conditions do not change dramatically over short term, time series models, which use past history of wind speed to predict future values, are found to perform reasonably well. They include moving average models such as ARMA, ARIMA and its variants fitted to the time series of wind speed [12–14], models based on artificial neural networks [13,15–17] and deterministic prediction models suitable for chaotically varying wind speed dynamics [18,19]. Most of these methods are capable of reasonably accurate predictions up to a few hours, but the range of predictability often varies significantly over topography and other local conditions [4].

Wind speed data usually exhibit long range correlations and f-ARIMA models are especially suited for making short to medium term forecasts of such data. Kavasseri and Sreetharaman [14] have applied f-ARIMA models to forecast hourly average wind speeds up to a period of two days ahead, with an improvement of prediction accuracy up to 42% compared to the elementary method of persistence. In this work we demonstrate that decomposition of the wind speed data into selected frequency components before applying the forecasting technique can dramatically improve the accuracy and longevity of prediction. The decomposition of wind speed data is achieved by the use of wavelet transform technique, while the actual forecasts on the component series are made by simple prediction tools such as auto-regressive (AR) model or f-ARIMA model.

2. AR and f-ARIMA models of prediction

A popular model for prediction of time series is the autoregressive (AR) model which uses a linear combination of p past observations and a random error. An AR-model AR(q) of order p has the form,

$$x_t = c + \sum_{i=1}^{p} \phi_i x_{t-i} + \varepsilon_t$$

where ϕ_i s are suitably chosen coefficients, c is a constant and ε_t is

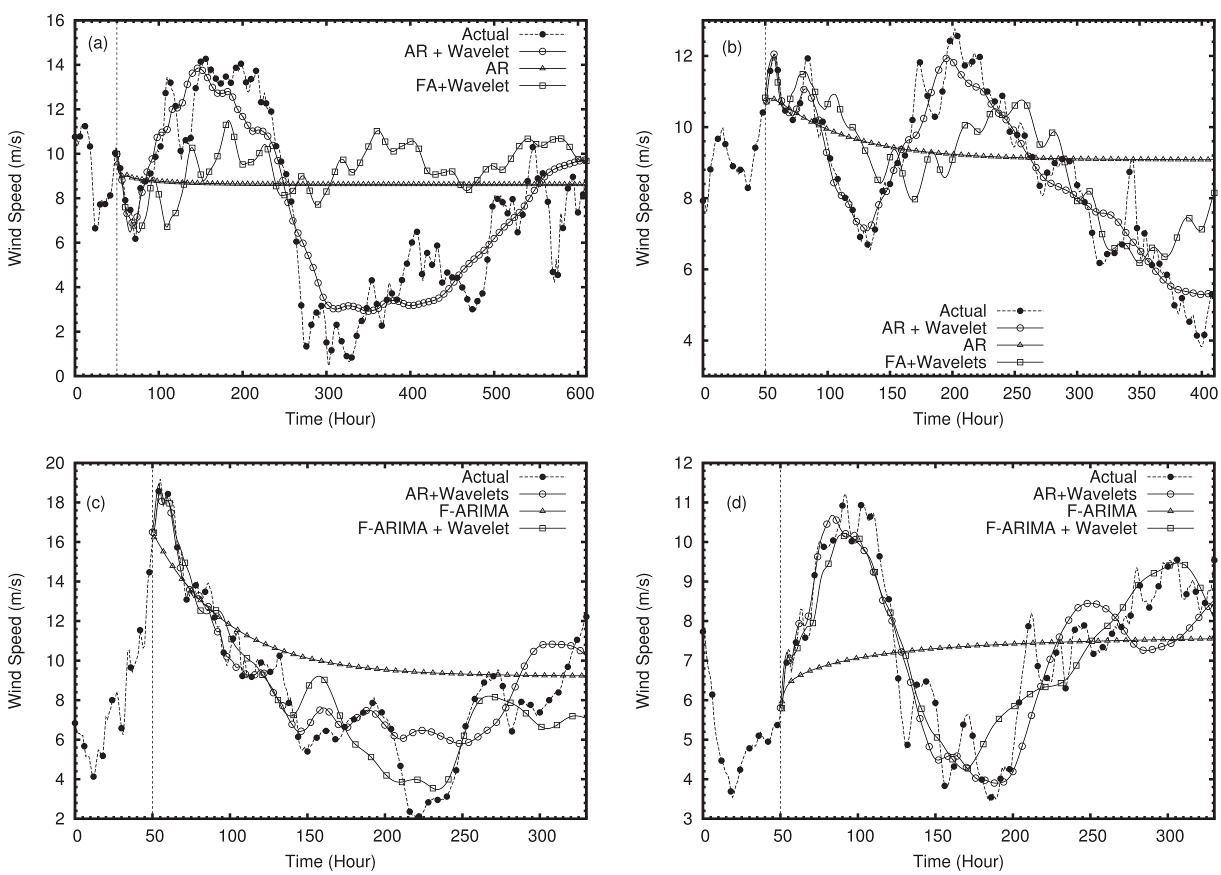

Fig. 2. Comparison of predicted values with actual data for AR and f-ARIMA models with and without wavelet decomposition. (a) Latitude: 44.34406°N Longitude: 99.61266°W, prediction start time: 2004-12-26 12:10:00 (b) Latitude: 45.39850°N Longitude: 103.51002°W, prediction start time: 2006-03-21 12:10:00 (c) Latitude: 44.95404°N Longitude: 96.60688°W, prediction start time: 2005-09-22 12:10:00 (d) Latitude: 38.67878°N Longitude: 98.59783°W, prediction start time: 2004-01-31 12:10:00.