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Time series prediction using artificial wavelet neural network and multi-resolution analysis: Application to wind speed data

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A B S T R A C T

The aim of this work is to develop a prediction method for renewable energy sources in order to achieve an intelligent management of a microgrid system and to promote the utilization of renewable energy in grid connected and isolated power systems. The proposed method is based on the multi-resolution analysis of the time-series by means of Wavelet decomposition and artificial neural networks. The analysis of predictability of each component of the input data using the Hurst coefficient is also proposed. In this context, using the information of predictability, it is possible to eliminate some components, having low predictability potential, without a negative effect on the accuracy of the prediction and reducing the computational complexity of the algorithm. In the evaluated case, it was possible to reduce the resources needed to implement the algorithm of about 29% by eliminating the two (of seven) components with lower Hurst coefficient. This complexity reduction has not impacted the performance of the prediction algorithm.

1. Introduction

The renewable energy sources (RES) are emerging as one of the best alternatives for sustainable electricity generation. The transition of the traditional energy systems towards renewable sources is required to reduce green-house gas emissions, and consequently to decelerate the global warming [1,2]. Different types of RES technologies are nowadays available for electricity generation. The wind turbines and the photo-voltaic modules are profitable alternatives for areas with high electricity costs, and are promoted by governments to reinforce the future smart grid. In fact, these sources have experienced strong energy market growth in the past few years. The optimal integration of renewable sources, as they are intermittent, exhibit fundamental challenges including the energy storage, the power conversion and the prediction of the available power [3,4].

The performance and efficiency of the renewable energy systems are thoroughly related to the power flow management between all components of the system. The complete energy storage system for renewable sources is not still technologically and economically well developed. However, the overproduction and the demand management could be better performed if the RES power profile is known in advance. Nonetheless, the electricity production from wind energy has some particularities derived from the intermittent behavior of wind speed, e.g. the production profile can not be adjusted satisfactorily to the one of the load demand; a balance of production and demand is then required which can be achieved using power reserves from other energy sources and/or a storage system support [5,6]. Scientific and industrial research efforts are unceasing to develop more accurate and reliable forecasting tools to mitigate the problem of irregularity in the RES power production [7]. The aim of those efforts seeks specially short term forecast and their applications on wind power management; they would enable e.g. the scheduling of the energy requirements for a given period (planning and delivering), solving more accurately and safely the micro-grid constraints and the schedule of maintenance [8–10].

Profiles of the available power of wind and solar sources depend on the geographic location, the season (or time of the year), the time of the day and other physical parameters. Wind speed modeling using time series is usually used to analyze wind profiles to obtain the predicted values. In the context of local energy management, the study of time series by means of a predictability analysis can be very helpful. Predictability analysis of time series

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has been introduced by Hurst [11] and can facilitate the selection of the prediction method which is essential for energy management.

In the literature, various approaches have been developed for wind speed prediction in renewable energy systems. Different prediction horizons have been studied; these methods have strengths and weaknesses and vary according to the context or environment of prediction. The framework prediction horizons are usually defined as follows: long-term (from one day to one week ahead), medium-term (from 6 h to one day ahead), short-term (from 30 min to 6 h ahead) and very short-term (few seconds to 30 min ahead) [12].

Three main categories of wind forecasting are frequently related in the literature: the statistical, the physical and the hybrid approaches [12,13]. Statistical approaches consist of time-series prediction based on historical data. These techniques have been the most popular methods in practice. Normally, the statistical analysis does not consider the meteorological data. In this group there are included the simple persistent model, the autoregressive models including the Auto Regressive (AR) process, the Auto Regressive Moving Average (ARMA), the Auto Regressive Integrated Moving Average Model (ARIMA) and the artificial neural networks (ANN). In Ref. [14] the ARMA model is used to predict the wind speed and direction. In Ref. [15] an ARMA-ARCH structure is proposed to predict the wind speed. A second subgroup can be identified in the statistical methods, usually involving artificial intelligence (AI) techniques. Other examples of wind speed prediction methods are the work related in Ref. [16] which proposes an AWNN, the Neural Network proposed in Refs. [17], the Wavelet and Neural Network model proposed in Ref. [18] and the Wavelet-PSO-ANFIS in Ref. [19].

The physical approaches are also known as Numerical Weather Prediction (NWP) methods; these techniques predict the wind speed by using meteorological (temperature, pressure, humidity, etc.) and topological information. The main disadvantages of NWP are their complexity of construction and operation, and their inaccuracy for short term forecast. The NWP combined with Gaussian Processes and Empirical Model has been employed to predict wind power in Refs. [20] and [21], respectively.

The last group of forecasting methods is the hybrid model, based on the combination of the two previous forecasting groups. Hybrid methods also give good results in short-time predictions. However, these methods are generally more complex and expensive to achieve. Some examples are the hybrid model proposed in Refs. [22]; and the hybrid model with Ensemble Empirical Mode Decomposition (EEMD) and the Support Vector Machine (SVM) presented in Ref. [23].

Long-term forecasting relies on NWP models, the statistical models used there focus on the short-term forecasts that can be useful in the hour-ahead utilities. The complex and nonlinear nature of wind speed and the ampleness of historical data put forward that AI-based techniques would be suitable candidates for wind speed and power production prediction.

This paper investigates the predictability analysis of the time-series of wind power and its application in a forecasting method based on the adaptive wavelet neural network (AWNN). The Hurst predictability and multi-resolution analysis (MRA) of time-series decomposition is applied to the wind power profile; this study shows that the wind speed behavior can be decomposed in fairly, mildly and definitely not predictable time series. A forecast strategy for the wind power is also proposed using a modified version of the adaptive wavelet neural network with the maximum overlap discrete wavelet transform (AWNN-MODWT). Knowing the decomposition predictability, the size of the forecasting tool can be optimized without accuracy degradation compared to the conventional methods proposed in the literature. This tool estimates the predictability score of each MRA component, with this information, the respective forecast AWNN can be eliminated. Consequently, a better generalization in the prediction network is obtained, avoiding over-fitting due to a large set of parameters. The proposed approach can easily be extended to the demand forecast. It can also be used for the identification of stochastic components in the production and consumption profiles, facilitating the implementation of control algorithms.

This document is organized in 5 sections. The theoretical aspects about the forecasting of time-series, the multi-step ahead forecasting concepts and the MRA-AWNN architecture are discussed in Section 2. The Hurst predictability analysis of wind speed is investigated in Section 3, the results are discussed in Section 4. Finally some concluding remarks are presented in Section 5.

2. Theoretical background

The time-series is a sequence of numeric observations from a particular measured variable. These observations are usually made on a regular basis (days, months, years), but sampling may be irregular or not. To represent the time-series prediction process, consider a sequence $X_N = \{x_1, \ldots, x_N\}$ comprising N observations. The multi-step ahead prediction consists of predicting $\{x_{k+1}, \ldots, x_{k+h}\}$ values of X_N, where $k = 1, 2, \ldots, N$ is the index of x and $h > 1$ is the index corresponding to the number of points between the present and the future, usually called the prediction horizon [24].

A time-series analysis consists of building a model that represents a time-series; using this model the future values are predicted only from past values. The data are described by a possible linear or non-linear autoregressive process of the form:

$$x(k+h) = f[x(k), x(k-1), x(k-2), \ldots, x(k-n-1)] \tag{1}$$

were f is a function describing the relationship between the past values of x and the present.

Currently, multi-step ahead prediction consists of predicting the h next values of the time-series. This task is achieved by two deferent ways. The first one, called independent value prediction, consists of training a direct model to predict $x(k+h)$. The second strategy, called iterative method, consists of repeating one-step ahead predictions to the desired horizon; this principle is shown in Fig. 1. The iterative prediction only uses one model to forecast all the horizons needed; the objective is to analyze a short sequence of data, and try to predict the rest of the data sequence until a predefined time-step is reached [25]. The main drawback of this approach is that the error in nearest horizons can be transmitted to others horizons.

2.1. Time-series prediction using AWNN

The wavelet networks calculate a linear combination function of

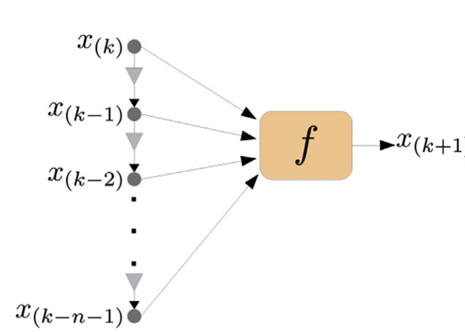

Fig. 1. Basic principle for one-step-ahead time series prediction ($h = 1$).