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Short term wind speed estimation in Saudi Arabia

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ABSTRACT

In this paper, three methods are used for the prediction of wind speed, 12 h ahead, based on 72 h previous wind speed values at three locations viz. Rawdat Bin Habbas (inland north), Juaymah (east coast), and Dhulom (inland western region) in Saudi Arabia. These methods are Particle Swarm Optimization (PSO), Abductory Induction Mechanism (AIM), and the Persistence (PER) model. The available data at each site was divided into three consecutive groups. The first 50% was used for training, the second 25% for validation, and the remaining 25% for testing. The validation data set was used to select the network architecture and other user defined parameters. The testing data was used only to assess the performance of the networks on future unseen data that has not been used for training or model selection. For each of the three methods, each of 12 networks was trained to produce the wind speed at one of the next 12 h. Relatively, Close agreements were found between the predicted and measured hourly mean wind speed for all three locations with coefficient of correlation R^2 values between 81.7% and 98.0% for PSO, between 79.8% and 98.5% for AIM and between 59.5% and 88.4% for persistence model. Both PSO and AIM methods underestimated WS values during most hours with an average value of 0.036 m/s and 0.02 m/s, respectively. However, persistence model overestimated the WS by an average value of 0.51 m/s. It is shown that the two developed models outperformed the persistence model on predicting wind speed 12 h ahead of time with slight advantage to the PSO method.

1. Introduction

Exploitation of wind power has become a center of attraction and implementation for all ranges of applications starting from roof top mounted wind turbines to multi-megawatt installed capacity grid connected wind farms. The reality behind this achievement is the commercial acceptability of the wind power technology and ease of installation and maintenance. Furthermore, wind energy is a clean, abundance, a free source of energy, available everywhere, and has no political or geographical boundaries. For proper and optimal utilization of wind power, accurate knowledge of wind speed variation with time, height, and in spatial domain over a region or a country is of prime importance. Accurate wind speed forecasts in future time domain greatly influence the wind energy as wind power density is directly proportional to the cube of wind speed. Moreover, the wind is a highly fluctuating meteorological parameter and varies with time of the day, season of the year, height above ground, and geographical location. Hence an accurate prediction of wind speed is a critical issue for wind energy yield and its cost. It is practically impossible to conduct wind measurements everywhere and at different heights all the time. Hence empirical, statistical, numerical, and modern learning methods are employed to estimate the wind speed in future time which in turn is used to estimate the energy yield and its cost.

The above requirement motivates researchers, engineers, and clean energy developers for the understanding, analysis, and prediction of wind speed and thereof power generation (Vogiatzis et al., 2004; Hepbasli and Ozgener, 2004; Shata and Hanitsch, 2006; Li et al., 2001a, 2001b). Several studies have been reported on the estimation and prediction of wind power produced by wind turbines (Pinson et al., 2003; Flores et al., 2005; Pallabazzer, 2004; Damousis et al., 2004; Cam et al., 2005). Bechrakis and Sparis (2004) developed a model for the estimation of wind speed at a location by utilizing the wind speed data available at nearby station and using sample cross correlation function (SCCF) of wind speed in time domain and an artificial neural network. The results showed that the higher the SCCF value between two sites, the better simulation achieved. Aksoy et al., (2004) proposed a new wind speed data generation method using wavelet transformation and compared the results with Weibull distributed random numbers, the first- and second-order autoregressive models, and the first-order Markov chain.

Dukes and Palutikof (1995) used Markov chain to estimate hourly wind speed with long return periods. Another Markov

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chain based study was conducted by Sahin and Sen (2001). Castino et al. (1998) coupled autoregressive processes to the Markov chain and simulated both wind speed and direction. Kaminsky et al. (1991) compared different alternative approaches used in the generation of simulated wind speed time series. Riahy and Abedi (2008) presented a linear prediction method for wind speed forecasting. The proposed scheme utilized the linear prediction method in conjunction with filtering of the wind speed waveform. The predicted values were compared with real wind speed data based on experimental results and demonstrated the effectiveness of the linear prediction method. Sfetsos (2000) used adaptive neuro-fuzzy inference systems and neural logic networks and compared performance with the autoregressive moving average models. Kitagawa and Nomura (2003) presented a wavelet-based method to generate artificial wind speed data. The Weibull distribution has been widely fitted to hourly mean wind speed data as can be seen from (Bagiorgas et al., 2011 and Rehman et al., 1994).

Mabel and Fernandez (2008) applied artificial intelligence techniques for the assessment of the wind energy output of wind farms in Muppandal, Tamil Nadu (India) using wind speed, relative humidity and generation hours as inputs and wind energy as output. The model accuracy was evaluated by comparing the simulated results with the actual measured values at wind farms and was found to be in good agreement. Artificial intelligence techniques such as neural networks, fuzzy logic, etc. are found to be more accurate as compared to traditional statistical models (Li et al., 2001a, 2001b and Ke'louwani and Agbossou, 2004). Further details about different methodologies used for the prediction wind speed and wind power can be found in Foley et al. (2012).

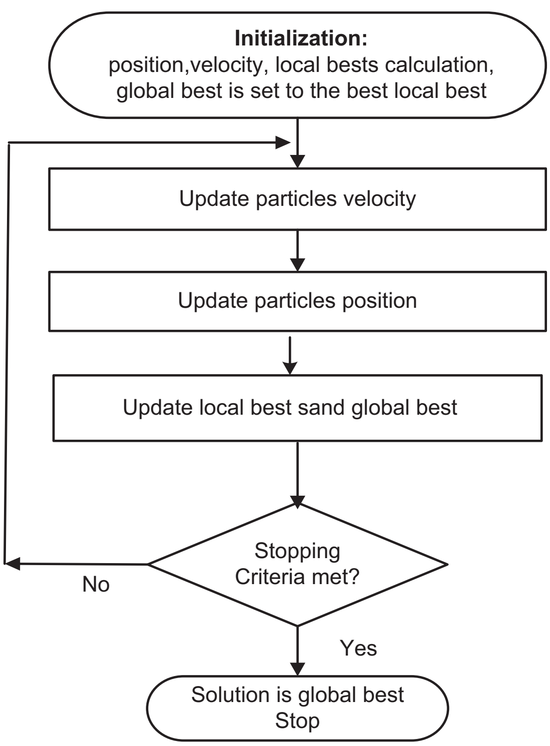

Fig. 1. Flowchart of the PSO training algorithm.

Numerical Weather Prediction (NWP) models incorporate information representing the outer scale geophysical variability through evolving boundary conditions and by assimilating observations of the current state of the atmosphere to predict flow characteristics. In addition, NWP models account for the effects of radiation, moist convection physics, land surface parameterizations, atmospheric boundary layer physics closures, and other physics packages. Wind power prediction is also approached by means of numerical/physical and statistical prediction models. The large-scale flow is modeled by an NWP model such as High Resolution Limited Area Model (HIRLAM) of the Danish Meteorological Institute (DMI) (Landberg, 2001). In this model the wind is transformed to the surface using the geostrophic drag law and the logarithmic profile (Landberg, 2001). Physical models are based on topography, terrains, local temperature and pressure to estimate more accurately the wind speed and subsequently the energy potential (Landberg, 1994). More precisely, two state-of-the-art atmospheric numerical models exist. These models are: the SKIRON regional atmospheric system (Kallos, 1997; Papadopoulos et al., 2001), and Eta/NCEP (Janjic, 1994). A very extended dynamical down scaling model is the PSU/NCAR fifth generation Mesoscale Model (MM5) which calculates atmospheric characteristics in a regional scale (NCAR, 2011). In wind resource assessment, the MM5 output is frequently used as initial and boundary conditions of microscalar models which insert local considerations in the mesoscalar simulation (Fueyo et al., 2010; Pepper and Wang, 2007; Stathopoulos et al., 2013). Ehrhard et al. (2000) used a mesoscale model to provide lateral boundary conditions for their microscale wind field model, MIMO. In addition they imposed the mesoscale flow on the microscale model by interpolating a steady state solution onto the fine grid and adjusting the interpolated flow with known similarity functions.

In this paper we compare the performance of Particle Swarm Optimization (PSO) and AIM with the persistence model on short term wind speed prediction in Saudi Arabia. The models inputs are wind speed at the previous 72 h while the output is the wind speed at one of the 12 h ahead. The remainder of this paper is organized as follows: Section 2 discusses in details the PSO and AIM algorithms, Section 3 provides description of wind speed data and the respective data collection sites, Section 4 shows the implementation set up. Section 5 discusses the results, and section 6 concludes the paper.

2. Description of the methods used in the study

2.1. Particle Swarm Optimization (PSO) algorithm

The PSO was motivated by the act of insect swarming, fish schooling, and bird flocking (Kennedy and Eberhart, 1995), It includes several individuals (called particles) that keep refining their position in the space of the problem at hand. Every particle is a solution to the problem, and is specified by its position in the space. The positions of particles are changed in a high dimensional space to find a better position. The PSO algorithm is initialized

Table 1
Site specific information of data collection stations.

Location	Latitude (deg)	Longitude (deg)	Altitude (m)	From date	To date	No. of records
Rawdat Bin Habbas	29° 38'	43° 29'	443	1/1/2006	12/31/2009	35,064
Juaymah	26° 46'	49° 53'	0	7/1/2006	4/30/2009	24,480
Dhulom	22° 12'	42° 03'	1117	11/1/1998	10/31/2002	34,560