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A novel adaptive approach for hourly solar radiation forecasting

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ABSTRACT

Solar radiation forecasting is an important part of planning and sizing of a photovoltaic power plant. Yearly measured hourly solar radiation data on the surface of a region include both stochastic and deterministic behaviors. The deterministic part comes from the solar geometry whereas the stochastic part is occurred due to random atmospheric events such as the motion of clouds etc. Moving from these facts, in this paper two different adaptive approaches are developed and tested for hourly solar radiation forecasting. In first approach, the data is separated into seasons. For winter and summer season it is thought that linear predictors work better due to rare alterations for short time periods. For these seasons linear prediction approach is adopted and used. On the other hand bigger alterations are most probable for spring and fall seasons. Therefore, for these seasons an empirical method is employed. In second approach, clearness index is considered as a decision maker to decide whether linear or empirical method will be used as a predictor. This decision is adopted for each prediction. It is obtained from the results that such an adoptive method outperforms non adoptive ones.

1. Introduction

Increasing energy demands together with rising conventional fuel costs and environmental awareness made renewable energy sources very popular in this decade [30]. Among others solar energy is one of the most important renewable energy sources. While it is possible to generate clean energy production from the solar radiation at the surface of a region, the variability of surface radiation levels caused by atmospheric processes decreases the reliability of the solar power production and increases the associated integration costs to the power grid [9]. In recent times the number of larger solar installations; both large scale photovoltaic and also concentrated solar thermal plants are considerably increased due to financial support of the governments. In order to first influence financial backers to participate in their development, and also to potentially compete in the electricity markets, better solar energy prediction models are required [16]. Furthermore, accommodating higher penetration levels of solar power into a new generation of power grid portfolios requires the use of increasingly more accurate forecasting systems in order to reduce backup reserves and improve unit commitment associated with power generation variability [8,18,23]. To improve the accuracy of prediction, a huge number of studies are performed. Among them, Artificial Neural Networks (ANN) [29], Adaptive Neuro-Fuzzy Inference System (ANFIS) [25], Autoregressive (AR) [3], Autoregressive Moving Average (ARMA) [20], Hidden Markov Model [13], Fuzzy Logic [6], Lasso [38], Angstrom–Prescott equations [19,21,24], Linear Prediction Filters [14] and Multi-Dimensional Linear Prediction Filters [1] can be good examples for time series prediction approaches. On the other hand, the use of hybrid models has gained popularity as it takes advantage of different models [22,37]. The basic idea of the model combination in forecasting is to use each model's unique feature to capture different patterns in the data. Both theoretical and empirical finding suggests that combining different models can be an efficient way to improve the forecast performance [37].

Developed hybrid methods in the literature are exemplified as following Wu and Chan [37]: proposed a new hybrid model that contains two different methods in the prediction phase. Firstly, ARMA model is used to predict the stationary residual series and then the controversial Time Delay Neural Network (TDNN) is applied to do the prediction. Their simulation results showed that this hybrid model can take the advantages of both ARMA and TDNN and gives better results [37]. Voyant et al. [34] presented a novel technique to predict global radiation using a hybrid ARMA/ANN model. This model has been used to forecast the hourly global

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radiation for five places in Mediterranean area and gave better results than the conventional one [34]. Bhardwaj et al. [5] proposed the combination of Hidden Markov Model (HMM) and Generalized Fuzzy Model (GFM) for solar radiation forecasting. In this work continuous density, HMM with Pearson R model is utilized for the extraction of shape based clusters from the input meteorological parameters and it is then processed by the GFM to accurately estimate the solar radiation [5]. Huang et al. [16] described a new and efficient method capable of forecasting 1-h ahead solar radiation during cloudy days. The method combines an autoregressive (AR) model with a dynamical system model and gives better results than both [16]. Mostafavi et al. [26] introduced a hybrid approach to predict global solar radiation. The solar radiation was formulated in terms of several climatological and meteorological parameters and monthly data collected for 6 years in two cities of Iran were used to develop GP/SA-based (genetic programming (GP) and simulated annealing (SA)) models. They showed that this method notably outperform the existing models [26].

Benmouiza and Cheknane [4] presented a hybrid model that includes k-means and nonlinear autoregressive neural network models. k-means algorithm is used to extract useful information from the data with the aim of modeling the time series behavior and find patterns of the input space by clustering the data. Nonlinear autoregressive (NAR) neural networks are powerful computational models for modeling and forecasting nonlinear time series. In this approach, the advantages of both methods are used to obtain more successful approach to predict solar radiation [4]. Chu et al. [9] introduced novel smart forecasting models for Direct Normal Irradiance (DNI). These models combine sky image processing with Artificial Neural Network (ANN) optimization schemes. The forecasting models, are used to predict 1 min average DNI for specific time horizons of 5 and 10 min. The hybrid forecast models proposed in this work achieve statistically robust forecasting skills in excess of 20% over persistence for both 5 and 10 min ahead forecasts [9]. Marquez et al. [23] described a new hybrid method that combines information from processed satellite images with ANNs for predicting global horizontal irradiance (GHI) at temporal horizons of 30, 60, 90, and 120 min. The forecasting approach uses information gathered from satellite image analysis including velocimetry and cloud indexing as inputs to the ANN models [23]. Voyant et al. [35] proposed an original technique to model the insolation time series based on combining ANN and AR and ARMA model. While ANN by its non-linear nature is effective to predict cloudy days, ARMA techniques are more dedicated to sunny days without cloud occurrences [35]. Dong et al. [11] presented a new hybrid method that uses satellite image analysis and a hybrid exponential smoothing state space (ESSS) model together with ANN. Geostationary satellite images provide cloud information, allowing a cloud cover index to be derived and analyzed using self-organizing maps (SOM) while the ESSS model is used to forecast cloud cover index. Solar irradiance values are predicted via ANN by using cloud cover index [11].

Wang et al. [36] developed an optimized hybrid method by CS (Cuckoo Search) on the basis of the OP-ELM (Optimally Pruned Extreme Learning Machine), for predict clear sky and real sky global horizontal radiation. Experimental results show that the optimized hybrid method has a good prediction performance [36]. Chu et al. [10] introduced a standalone, real-time solar forecasting computational platform that integrates cloud tracking techniques using a low-cost fisheye network camera and ANN algorithms. They trained and validated the forecasting methodology with measured irradiance and sky imaging data collected for a six-month period, and applied it operationally to forecast both global horizontal irradiance and direct normal irradiance at two separate locations. Results show that the forecasting platform outperforms the reference persistence model for both locations [10]. Gala et al. [12] applied Support Vector Regression (SVR), Gradient Boosted Regression (GBR), Random Forest Regression (RFR) as well as a hybrid method to combine them to downscale and improved 3-h accumulated radiation forecasts provided by Numerical Weather Prediction (NWP) systems for seven locations in Spain. Their results show that hybrid artificial intelligence systems are quite effective and, hence, relevant for solar radiation prediction [12].

In this paper, a novel alternative adaptive method that combines the linear prediction filters and an empirical model is developed. Two different combining strategies are applied and effects of these strategies on prediction performances are investigated. In the first strategy, the method to be used is determined according to season. In winter and summer times linear prediction filters can be a good choice due to strong correlation with extraterrestrial radiation. This correlation foregrounds linear prediction filter for prediction. In the second strategy, on the other hand, the clearness index values are employed as decision maker. If the clearness index value is greater than a specified value, linear prediction filters otherwise empirical models are decided as the predictor. To test the performance of the approaches developed, solar radiation data of different regions (Afyonkarahisar, Ankara and Çanakkale) are used. The organization of the paper is as follows. The data used for this study are described in Section 2. The novel adaptive hybrid approach is explained in Section 3. Experimental results are given in Section 4. Finally, conclusions are explained in Section 5.

2. The description and evaluation of the data

In this study, solar radiation data from different regions (Afyonkarahisar, Ankara and Çanakkale) in Turkey are used. The regions used to test the performance of the proposed approaches are depicted in Fig. 1. The global solar radiations data belong to these regions are taken from Turkish State Meteorological Service (DMI). Some data (<1% of all data) were wrong measured (the values were bigger than calculated extraterrestrial values) or missing due to different external reasons. Such data are predicted using previous and future values of the data as a preliminary analysis. In the empirical method (see Section 3), extraterrestrial solar radiation values are critical. By definition, extraterrestrial radiation is the intensity of the sun at the top of the Earth's atmosphere and can be calculated using solar geometry for the region. It varies throughout the year because of the Earth's elliptical orbit, which results in an Earth-Sun varying distance during the year in a predictable way [1]. In this study, hourly extraterrestrial global solar radiations are calculated using the MDIC SOLPOS Calculator, which is available from the NREL website (http://www.nrel.gov/).

To apply linear prediction filters, the data to be used are converted into a 2-D matrix. Hocaoglu et al. [14] first proposed this 2-D representation of solar radiation data. The 2-D image obtained from the solar radiation data provides the tool for the image processing techniques on solar data. Fig. 2 illustrates the one year solar radiation time series and data are rendered as a two-dimensional matrix (Eq. (1)) and plotted as a surface mesh in Fig. 3, where the dimensions x, y, z, are hours of days, days of year, and solar radiation magnitudes, respectively.

$$X_{rad} = \begin{bmatrix} x_{11} & \ldots\ldots & x_{1n} \\ \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot \\ x_{m1} & \ldots\ldots & x_{mn} \end{bmatrix} \tag{1}$$

Illustration in Fig. 3 provides significant insight about the radiation pattern as a function of time. The informational insight is apparent from the sample surface plots and image visualizations