Renewable Energy 91 (2016) 434–441

Contents lists available at ScienceDirect

Renewable Energy

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

Hybrid solar irradiance now-casting by fusing Kalman filter and regressor

Hsu-Yung Cheng

Department of Computer Science and Information Engineering, National Central University, No.300, Jhongda Rd., Jhongli City, Taoyuan County, Taiwan

ARTICLE INFO

Article history:
Received 18 November 2015
Received in revised form
21 January 2016
Accepted 25 January 2016
Available online 4 February 2016

Keywords:
Solar irradiance
Prediction
Kalman filter
Regression

ABSTRACT

In this work, a hybrid solar irradiance now-casting mechanism is proposed. The proposed hybrid predictor fuses the results from both Kalman filter predictor and regressor predictor to benefit from the advantages of both techniques. A time-varying adaptive system function for Kalman filter is designed to deal with ramp-down events for more accurate prediction. Three fusion alternatives based on local root mean square error computation are proposed and compared. The experimental results have validated the effectiveness of the proposed method on a challenging dataset.

1. Introduction

Sustainable and renewable energy has been consistently promoted by governments and international organizations to alleviate the energy crisis dominated by fossil fuels and to act against negative effects induced by the growing emission of carbon dioxide in the atmosphere. Compared to finite quantities of fossil fuels, solar light, winds and waves are energy resulting from planet activities and enjoy the advantage of being sustainable. In addition, the production and use of renewable energy involves little emission compared to those produced by fossil fuels [1]. Although the characteristics of these sustainable energy sources are being unstable and intermittent, the attention toward these renewable forms of energy motivates the researchers to try to overcome the unstable nature of these energy sources [2].

Solar energy is one of the sustainable energy that receives growing attention in recent years. Photovoltaics (PV) are installed worldwide to provide clean and renewable electricity for residential, commercial or industrial uses. There is noticeable PV installation growth even in regions with moderate solar energy resources [3]. One of the crucial factors for the performance of PV systems is the availability of solar energy on ground surface that can be converted into electricity. Therefore, accurate solar irradiance prediction is very important for successful planning and operation of PV. Both medium-term prediction and short-term prediction schemes are desired by PV grid operators [4]. The prediction horizon of short-term to medium-term prediction ranges from a few hours to a few days [5–11]. For medium-term prediction, Mellit and Pavan [7] utilized present values of the mean daily solar irradiance and air temperature to forecast the solar irradiance on a base of 24 h. Hejase and Assi [8] used time-series regression with autoregressive integrated moving-average model for mean daily and monthly global solar irradiance prediction. Bacher et al. [9] applied adaptive linear time series models to predict hourly values of solar power for horizons of up to 36 h. Lorenz et al. [10] predicted regional PV power output based on European Centre for Medium-Range Weather Forecasts (ECMWF) up to three days ahead. Marquez et al. [11] built an hourly artificial neural network prediction model that took meteorological variables from the US National Weather Service's (NWS) forecasting database as input. Lynch et al. [12] estimated solar irradiance observations from a Numerical Weather Prediction model using a bank of 24 Kalman Filters which operate in tandem to predict the solar irradiance 24 h ahead. Martín et al. [13] discussed and compared the methods using autoregressive models and neural networks.

The prediction horizon for very short-term irradiance prediction or now-casting typically ranges from three to 15 min [14]. The PV operators are allowed to schedule, dispatch, and allocate alternative energy resources more effectively given the information of accurate very short-term prediction. For example, the operators can launch backup energy resources if they know that the available

E-mail address: chengsy@csie.ncu.edu.tw.

http://dx.doi.org/10.1016/j.renene.2016.01.077
0960-1481/

Nomenclature

$\widehat{I}^{(KF)}_{k+\Delta P}$	Predicted solar irradiance by Kalman filter for time instance $k+\Delta P$
$\widehat{I}^{(R)}_{k+\Delta P}$	Predicted solar irradiance by Regressor for time instance $k+\Delta P$
ΔP	Prediction horizon
I_k	Ground truth solar irradiance at time instance k
Δt	Time window for local root mean square error computation
A_k	All-sky image at time instance k
ΔT	Time interval for feature extraction
$MEAN_{NC}$	Mean of number of cloud pixels in the all-sky images within time interval ΔT
VAR_{NC}	Variance of number of cloud pixels in the all-sky images within time interval ΔT
$MEAN_{GM}$	Mean value of gradient magnitude in the all-sky images within time interval ΔT
$MEAN_{IL}$	Mean value of intensity level in the all-sky images within time interval ΔT
$MEAN_{SI}$	Mean value of the accumulated intensity along the vertical line of sun in the all-sky images within time interval ΔT
$C_{RD}(k)$	Support vector machine classifier for ramp-down event forecasting
x_k	System state of Kalman filter at time instance k
y_k	Measurement state of Kalman filter at time instance k
F_k	System function of Kalman filter at time instance k
H_k	Measurement function of Kalman filter at time instance k
w_k	System noise of Kalman filter at time instance k
r_k	Measurement noise of Kalman filter at time instance k
Q_k	Process noise covariance of Kalman filter at time instance k
R_k	Measurement noise covariance of Kalman filter at time instance k
$\widehat{x}_{k\|k-\Delta P}$	Predicted state estimate of time k given the information of time $k-\Delta P$
$P_{k\|k-\Delta P}$	Predicted estimate covariance of time k given the information of time $k-\Delta P$
$\dot{I}_k$	The difference between I_k and $I_{k-\Delta P}$
$\tilde{y}_k$	Measurement residual of Kalman filter at time instance k
α_k	Adjusting factor for prediction refinement on ramp-down event
M_{RD}	Mean ramp-down value learned from training samples
$E^{(KF)}_k$	Local RMSE of Kalman filter predictor
$E^{(R)}_k$	Local RMSE of regressor predictor
θ	Threshold for the proposed hybrid predictor alternative 2
$[f_1,\cdots,f_n]$	The n dimensional input feature vector of the multiple regressor
$b_0,\cdots,b_n$	The coefficients of the multiple regressor

solar energy is going to drop in 10 min. Moreover, if the accurate amount of the drop can be forecasted, it helps reduce the overhead of backup storage. Chaabene and Ammara [15] used meteorological measurements to predict irradiance and temperature 5 min ahead by Neuro-fuzzy dynamic model. Kalman filter is also used as a statistical post-processing tool in the work by Rincón et al. [16]. In addition to Kalman filter, regression analysis techniques are also found in related works [16–20]. Reikard [18] used regressions in logs, autoregressive integrated moving average, and unobserved components models. The works by Fu et al. [19] and Cheng et al. [20] both utilized regression models to predict solar irradiance from five to 15 min ahead.

Satellite images and numerical weather prediction information are popular materials used for wide-range or mid-term solar irradiance prediction. However, for irradiance now-casting, more refined spatial and temporal resolution of prediction is required. When data for different parts of a PV park needs to be collected and processed, satellite images lack sufficient resolution to do this. A large PV park would appear as only one pixel in satellite images. Also, it is generally not feasible to update a satellite image every minute. To acquire more information that can complement the insufficiency of resolution of satellite images, all-sky cameras are introduced and applied in the research area of irradiance now-casting. In Refs. [21], a review is presented to analyze irradiance prediction methods based on statistical approaches and cloud images. Sabburg and Wong [22] conducted an evaluation on a sky camera system to study the effect of clouds. Pfister [23] surveyed the impact of cloud coverage on surface solar irradiance using all-sky cameras. Marquez [14] proposed an approach to compute cloud fractions and forecast Direct Normal Irradiance (DNI). Fu et al. [19] extracted all-sky image features that are relevant to irradiance now-casting. Cheng et al. [20] developed a bi-model prediction mechanism based on the occlusion conditions of the sun in the all-sky images. They also refined the predicted result according to a ramp-down event forecasting scheme. In this work, a hybrid solar irradiance now-casting mechanism is proposed. The proposed hybrid predictor integrates the Kalman filter predictor and regressor predictor to benefit from the advantages of both techniques. A time-varying adaptive system function for Kalman filter is designed to deal with ramp-down events. Effective fusion processes are proposed to fuse the two different predictors to achieve more accurate prediction.

2. System framework

As illustrated in Fig. 1 (a), the goal of the system is to obtain the predicted irradiance $\widehat{I}_{k+\Delta P}$ using the information of current and previous ground truth irradiance$I_{k-\Delta T}$, $\cdots$, I_{k-1},I_k and all-sky images$A_{k-\Delta T}$, $\cdots$, A_{k-1},A_k. Fig. 1 (b) shows the proposed system modules. The ground truth irradiance readings and the all-sky image features are the input of the regressor predictor. The regressor predictor outputs the prediction $\widehat{I}^{(R)}_{k+\Delta P}$. The Kalman filter predictor generates the prediction $\widehat{I}^{(KF)}_{k+\Delta P}$ according to the current and previous ground truth irradiance and the result of ramp-down event forecasting. Finally, the results of the two predictors are fused to give us the final prediction.

The all-sky image features are extracted from $A_{k-\Delta T}$, $\cdots$, A_{k-1},A_k as suggested in Ref. [19]. The extracted features include the mean and variance of number of cloud pixels ($MEAN_{NC}$ and VAR_{NC}), the mean value of gradient magnitude ($MEAN_{GM}$), the mean value of intensity level ($MEAN_{IL}$), and the mean value of the accumulated intensity along the vertical line of sun ($MEAN_{SI}$) in $A_{k-\Delta T}$, $\cdots$, A_{k-1},A_k.

The all-sky image features along with the history ground truth