Solar Energy 188 (2019) 1369–1379

Contents lists available at ScienceDirect

Solar Energy

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

Data Article

# OpenSolar: Promoting the openness and accessibility of diverse public solar datasets

Cong Feng[a], Dazhi Yang[b], Bri-Mathias Hodge[c,d], Jie Zhang[a,*]

[a] Department of Mechanical Engineering, The University of Texas at Dallas, Richardson, TX 75080, USA
[b] Singapore Institute of Manufacturing Technology, Agency for Science, Technology and Research (A*STAR), Singapore
[c] National Renewable Energy Laboratory, Golden, CO 80401, United States
[d] Department of Electrical, Computer and Energy Engineering, The University of Colorado Boulder, Boulder, CO 80309, United States

ARTICLE INFO

*Keywords:*
Solar data openness
R
Python
Machine learning
Data-driven

ABSTRACT

Observational solar data is the foundation of data-driven research in solar power grid integration and power system operations. Compared to other fields in data science, the openness and accessibility of solar data is lacking, which prevents solar data science from catching up with the emerging trends of data science (e.g., deep learning). In this paper, `OpenSolar`, a package with both R and Python versions, is developed to enhance the openness and accessibility of publicly available solar datasets. The `OpenSolar` package provides access to multiple types of solar data, primarily from four datasets: (1) the National Renewable Energy Laboratory (NREL) Solar Power Data for Integration Studies dataset, (2) the NREL Solar Radiation Research Laboratory dataset, (3) the Sheffield Solar-Microgen database, and (4) the Dataport database. Unlike other open solar datasets that only contain meteorological data, the four datasets in the `OpenSolar` package also contain behind-the-meter power data, sky images, and solar power data with satisfactory temporal and spatial resolution and coverage. The overview, quality-control methods, and potential usage of the datasets, in conjunction with sample code implementing the `OpenSolar` functions, are described in this paper. The package is expected to assist in bridging the gaps between the research fields of solar energy, power systems, and data science.

## 1. Introduction

With the rapid development of sensor, wireless transmission, and network communication technologies, large amounts of data have been accumulated in the power and energy domain, which has brought benefits of (i) enhancing system stability & reliability, (ii) increasing asset utilization & efficiency, and (iii) better communications between customers and utilities (Zhou et al., 2016; Tu et al., 2017). Solar energy data is a core element of informed solar energy decision-making, such as target setting & policy making (Cox et al., 2018), resource assessment (Kleissl, 2013), investment (Ondraczek et al., 2015), forecasting (Kleissl, 2018), and solar power integration & grid management (Pohekar and Ramachandran, 2004). Nevertheless, solar data public availability for research purposes lags behind other fields (e.g., image processing) due to several impediments, such as business/security concerns and institutional/personal inertia (Pfenninger et al., 2017). Great efforts have been made to increase the transparency and availability of solar energy data (Pfenninger et al., 2018), which has lead to over 40 datasets worldwide (Sengupta et al., 2017).

To further facilitate solar data research, promoting the availability and accessibility of solar data sets is highly encouraged by the solar energy community (Yang et al., 2018). For example, some well-known solar datasets, like the Surface Radiation Budget Network (SURFRAD) (Augustine et al., 2000) and National Solar Radiation Data Base (NSRDB) (Sengupta et al., 2018), were developed and released to the public. Solar forecasts have also become accessible from online platforms, such as the IBM Physical Analytics Integrated Data Repository and Services (PAIRS) (Lu et al., 2016). Despite the wealth of publicly available datasets, it is still challenging for users to easily access and pre-process these datasets. To this end, packages and libraries of R and Python functions, two of the most popular languages in data science and machine-learning, have been developed. For example, Lamigueiro et al. (2018) developed an R package, `meteoForecast`, to provide access to several Numerical Weather Prediction services. Yang (2018) developed an R package, `SolarData`, to get access to meteorological solar irradiance datasets. `PVLIB`, a Python package developed by Sandia National Laboratories, provides various solar data and simulation functions (Holmgren et al., 2015). However, most of the datasets

* Corresponding author.
*E-mail address:* jiezhang@utdallas.edu (J. Zhang).

https://doi.org/10.1016/j.solener.2019.07.016
Received 13 March 2019; Received in revised form 10 May 2019; Accepted 3 July 2019
Available online 19 July 2019

accessed through current packages only include climatic and meteorological data, which does not always meet the needs of the solar research community due to the lack of (i) solar power data, (ii) behind-the-meter photovoltaic (PV) data, (iii) time-synchronous heterogeneous data that can be used for solar coordination research, such as data from electrical vehicles, appliances, water and gas, and (iv) data in other formats, such as sky images, which offer opportunities to take full advantage of deep learning techniques.

In this paper, a new package, `OpenSolar` (version 1.0), which has both R and Python versions, is developed to increase the openness and accessibility of diverse publicly available datasets. Ten functions are provided in the package to download, quality control (QC), read in, preprocess, and model with the data. In this paper, all the code examples used to demonstrate the functions are written in R, which can be found in the Github repository.[1,2] The `OpenSolar` package should first be installed and loaded before calling its functions. The installation code and examples of function calls in the R package are shown as:

Four datasets are included in the package, which are the National Renewable Energy Laboratory (NREL) Solar Power Data for Integration Studies (SPDIS) dataset (GE Energy, 2010; Lew et al., 2013; Miller et al., 2014; Bloom et al., 2016), NREL Solar Radiation Research Laboratory (SRRL) dataset (Stoffel and Andreas, 1981), Sheffield Solar-Microgen Database (Sheffield Solar, 2016), and the Dataport Database (Pecan Street Inc, 2019). `OpenSolar` has the following advantages:

```
library(devtools)
install_github('UTD-DOES/OpenSolar')
# load the package and list the functions
library(OpenSolar)
lsf.str('package:OpenSolar')
## Dataport.get : function (usrname, pswd, hsid, timeres, qc)
## Dataport.meta : function (usrname, pswd, qc, ifdownload, root_save)
## Microgen.read : function (root_data)
## MLForecast : function (data_inputmain, n_step, p_ratio)
## SPDIS.download : function (root_data, list_st_download, ifunzip, actualonly)
## SPDIS.read : function (root_data, name_st, list_files, readall)
## SRRL.download : function (root_data, date_start, date_end, skyimg, tmseries, i
funzip, ifunique)
## SRRL.read : function (timestamp, root_data, returnRGB, processraw, processadv)
```

(1) The datasets accessed by `OpenSolar` contain diverse variables, including meteorological variables, simulated solar PV power, behind-the-meter PV measurements, behind-the-meter appliance measurements, sky images, etc.
(2) The datasets have satisfactory spatial or temporal coverage and resolution (e.g., Dataport contains 1 min data and SPDIS covers the entire US).
(3) The functions are well-packaged so that it is easy to access and preprocess the datasets.
(4) Example use cases are provided in the package for demonstration and benchmarking purposes.

The remainder of the paper is organized as follows. The four datasets and relevant R code are described sequentially in Sections 2–5. Section 6 introduces the modeling and visualization of the machine-learning based short-term solar forecasting benchmarks. Concluding remarks and ideas for future work are given in Section 7. The code for example usage and the Python version of the package are detailed in the Appendices.

[1] https://github.com/UTD-DOES/OpenSolar.
[2] https://zenodo.org/badge/latestdoi/155460712.

## 2. NREL Solar Power Data for Integration Studies (SPDIS) dataset

### 2.1. Overview

The NREL SPDIS dataset was originally created for large-scale renewable energy integration studies, including the Western Wind and Solar Integration Study (GE Energy, 2010; Lew et al., 2013; Miller et al., 2014) and Eastern Renewable Generation Integration Study (Bloom et al., 2016). The SPIDS dataset consists of 1-year (2006) data of 5020 utility scale/distributed PV locations, covering 47 states (excluding Alaska, North Dakota, and Hawaii) of the United States. The distribution and capacities of PV locations are visualized in Fig. 1. It is found that Florida (593), California (405), and Georgia (332) are the three states with the most PV locations in this dataset. The number of distributed PV locations is larger than centralized PV plants, which is illustrated from the PV capacity distribution.

The SPDIS has 5-min simulated PV power data and hourly 1-day-ahead (1DA) and 4-h-ahead (4HA) PV power forecasts. The PV power is generated based on irradiance from the NSRDB Physical Solar Model (PSM) V2.0 version,[3] which was developed based on a satellite cloud cover model by the State University of New York (GE Energy, 2010). The 1DA forecasts were generated by 3TIER based on numerical weather prediction (NWP) simulations (Brower et al., 2009), while 4HA forecasts are produced by using a persistence of cloudiness method (Lew et al., 2013).

### 2.2. Potential usage

Created for solar power integration studies, SPDIS has an extensive spatial coverage. Based on a meteorological dataset (i.e., NSRDB), SPDIS provides solar power information with spatial diversity, which is necessary for large-scale solar power integration research. For example, SPDIS has provided opportunities for system-level operation studies (GE Energy, 2010; Lew et al., 2013; Miller et al., 2014; Bloom et al., 2016), power market design (Tewari et al., 2011), energy storage research (Pandžić et al., 2015; Su and Gamal, 2013), among other applications.

SPDIS can also be used to develop solar forecasting methods, which are critical for power system operations. SPDIS has been used to investigate solar forecasting by considering spatial hierarchy (Yang et al., 2017), temporal hierarchy (Yang et al., 2017), and ensemble forecasting (Yang and Dong, 2018). The generality of the dataset helps explore statistical characteristics of solar forecasting, such as forecas error metric development (Zhang et al., 2015), solar forecast error analysis (Zhang et al., 2014; Zhang et al., 2013), and solar forecast benefit assessment (Martinez-Anido et al., 2016). To the best of our knowledge, SPDIS has the largest spatial extent among publicly available solar power datasets, which is beneficial to large-scale solar power integration and general forecasting pattern assessment (Feng et al., 2019).

[3] https://nsrdb.nrel.gov/current-version.

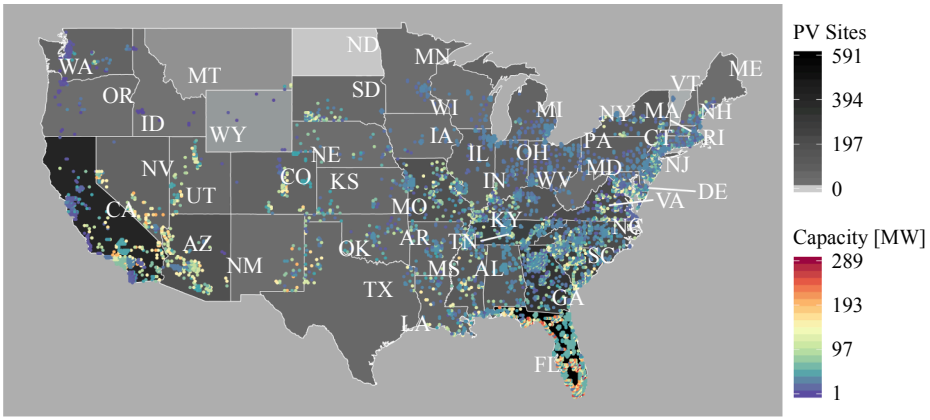



**Fig. 1.** Distribution map of PV locations in the SPDIS dataset. The unit of capacity is MW.

### 2.3. Data pre-processing

SPDIS can be downloaded by state through HTTPS connections. The easiest way is by clicking the corresponding download links from the NREL SPDIS website.[4] A more efficient approach is performing bulk download through the URL of the dataset. In the `OpenSolar` package, the `SPDIS.download()` function provides a neat front end to efficiently batch download SPDIS data by state. The following code downloads, unzips, and filters data of PV locations in Alabama and Arkansas:

After uncompressing the zip file into CSV files, a folder with the state's name is created, containing PV power time series (and PV power forecasting time series if `actualonly` is set to be FALSE). While reading a CSV file is easy by using `read.table()` or `read.csv()` function, importing all the CSV files might be tedious. The `OpenSolar` package provides a function, `SPDIS.read()`, to import PV power time series from a particular state and create a data frame. The function also stores locational information in another data frame. We have found this function to be useful for data pre-processing, especially for large spatial analysis.

```
# specify directory to save files
root_save <- getwd()
# list files in the direcotry
list.files(root_save)

## character(0)

# specify the states and download
st <- c('Alabama', 'Arkansas')
SPDIS.download(root_save, st, ifunzip = T, actualonly = F)
# check files in the directory after the download
list.files(root_save)

## [1] "Alabama"  "Arkansas"
```

```
# specify your data directory
root_data <- 'your data directory'
list_data <- SPDIS.read(root_data, name_st = 'Texas', list_files = NA, readal
l=T)
# extract time series and location information
data_ts <- list_data[[1]]
data_linfo <- list_data[[2]]
head(data_ts[,1:3], n = 3)

##        LocalTime Location1_Power[MW] Location2_Power[MW]
## 1 01/01/06 00:00                   0                   0
## 2 01/01/06 00:05                   0                   0
## 3 01/01/06 00:10                   0                   0

head(data_linfo, n = 3)

##   Location Latitude Longitude Capacity [MW]
## 1        1    32.05    -94.15            95
## 2        2    32.05    -94.35            27
## 3        3    32.35    -94.25           122
```

[4] https://www.nrel.gov/grid/solar-power-data.html.

### 2.4. Quality control

The SPDIS dataset has already been pre-processed by a two-stage QC: the NSRDB QC and PV output QC. The NSRDB QC is performed by (i) restricting solar zenith angle to be less than 80°, (ii) setting negative irradiance to be zero, (iii) excluding missing values, and (iv) determining sky condition by cloud types (Habte et al., 2017; Sengupta et al., 2018). In terms of PV output QC, PV output is simulated using PVWatts (Dobos, 2014), which takes sub-hourly variability, derating factors, PV system installation parameters, site selection, temporal trends, coincident relationships with wind and load, and forecastability into consideration. More details of the PV output QC can be found in (GE Energy, 2010).

## 3. NREL Solar Radiation Research Laboratory (SRRL) dataset

### 3.1. Overview

The NREL SRRL[5] has been collecting continuous solar measurements at NREL's South Table Mountain Campus (longitude: 105.18°W, latitude 39.74°N, elevation 1,828.2 m), Golden, Colorado since 1981. More than 80 instruments have been installed, including pyranometers, pyrheliometers, pyrgeometers, photometers, and spectroradiometers, which compose the Baseline Measurement System (BMS).[6] The collected data have both high temporal-resolution (varying with measuring time and device) and diverse features. In addition to meteorological and climatical data, the SRRL dataset also contains two sets of total sky images, which are taken by a Yankee Total Sky Imager (TSI-800) and an EKO All Sky Imager (ASI-16). Both sets of TSIs have sky image snapshots and cloud-analyzed images with 10-min resolution. The TSI-800 has captured TSIs with a resolution of $288 \times 352$ pixels since 2004-07-14, while the ASI-16 started to record TSIs with a higher resolution of $1536 \times 1536$ pixels on 2017-09-26.

### 3.2. Potential usage

The NREL SRRL dataset is recognized for its high quality, which has been used as the benchmarking standard to validate the quality of other datasets with measured or simulated data, such as NREL's Surface Radiation Budget Network dataset, NOAA's Integrated Surface Irradiance Study dataset (Anderberg and Sengupta, 2014), and the NSRDB (Habte et al., 2017). SRRL has also been used to verify the effectiveness of irradiance models (Vick et al., 2012), spectral distribution derivation (Myers, 2012), and transposition models (Xie et al., 2018).

Due to its wide range of measurements, SRRL has been extensively used in solar energy research, such as solar forecasting (Reikard, 2009), and solar energy statistical analysis (Lave and Kleissl, 2010; Kang and Tam, 2013), PV panel design optimization (Lave and Kleissl, 2011), solar energy and electrical vehicle coordination (Saber and Venayagamoorthy, 2010; Saber and Venayagamoorthy, 2011). Unique among publicly available datasets, the sky images in SRRL dataset provide special input features for sky image processing based solar forecasting, including pixel red blue ratio statistics (Feng et al., 2018; Feng and Zhang, 2018; Feng et al., 2017b), cloud coverage (Saade et al., 2014), and cloud classes (Zhen et al., 2015).

### 3.3. Quality control

The SRRL QC that has already been performed on the dataset is twofold, including sky image QC and ground-based measurement QC. The sky image QC consists of selecting the high-resolution sky image set and pre-processing sky images. For the ground based measurements, there are over 190 measured variables collected from 80+ devices, which are maintained under NREL's SERI-QC methodology (Stoffel and Andreas, 1981).

Considering the higher resolution and more advanced quality-control algorithms, the ASI-16 sky images are included in this package. Two sky images are taken by the ASI-16 every 10 min, a normal exposed original image (named with an '_11_NE' extension) and an underexposed original image (named with a '_12_UE' extension). The angle offset of the original images is rectified so that the calibrated images (with '_11' and '_12' extensions, respectively) are in the same direction as a map, i.e., North at the top. The pixels with zenith angles larger than 70° are discarded from the images to avoid hazy sky and obstacle presence (Luiz et al., 2018). In addition to the original and calibrated images, two sets of cloud-detected images are also provided based on the blue/red and blue/green ratio (BRBG) algorithm and the cloud detection and opacity classsifcation (CDOC) algorithm (Ghonima et al., 2012) (named with 'BRBG' and 'CDOC' extensions, respectively). The BRBG algorithm classifies cloud pixels by an RGB threshold. The CDOC algorithm employs a clear sky library to improve the classification (both thin cloud pixels and thick cloud pixels) accuracy and removes the pixels affected by sun glaring (shown as the black triangle around the sun in Fig. 2(f)). A set of 6 example images of each variety are shown in Fig. 2.

SERI-QC performs post-measurement quality and uncertainty assessment to ensure that the data is within established boundaries and follows plausible patterns (Maxwell et al., 1993). The SERI-QC has been widely applied for solar irradiance QC (Zell et al., 2015; Diagne et al., 2014; Gueymard and Wilcox, 2011), and the quality-assured SRRL dataset is often used as ground-truth to calibrate other datasets (Anderberg and Sengupta, 2014; Lave and Kleissl, 2010).

### 3.4. Data pre-processing

With the inclusion of rich climatic and meteorological variables, SRRL can support a number of different types of solar research. Therefore, a function called `SRRL.download()` in the `OpenSolar` package was developed to access the wealth of variables, collected from over 80 devices. The variable and device information can be found on the SRRL BMS instrument description webpage.[7] In addition to numerical measurements, the `SRRL.download()` function can also download ASI-16 sky images. Numerical time series and sky images can be downloaded together or seperately based on different uses, controlled by the `skyimg` and `tmseries` parameters. The sky images are zipped by day, which can be uncompressed by the function. Redundant images, except for raw images and the CDOC-processed images, are removed from the disk if the boolean parameter `ifunique` is TRUE. The following code provides an example of downloading both time series measurements and sky images within a time range.

[5] https://www.nrel.gov/esif/solar-radiation-research-laboratory.html.
[6] https://midcdmz.nrel.gov/srrl_bms/.
[7] https://midcdmz.nrel.gov/srrl_bms/.

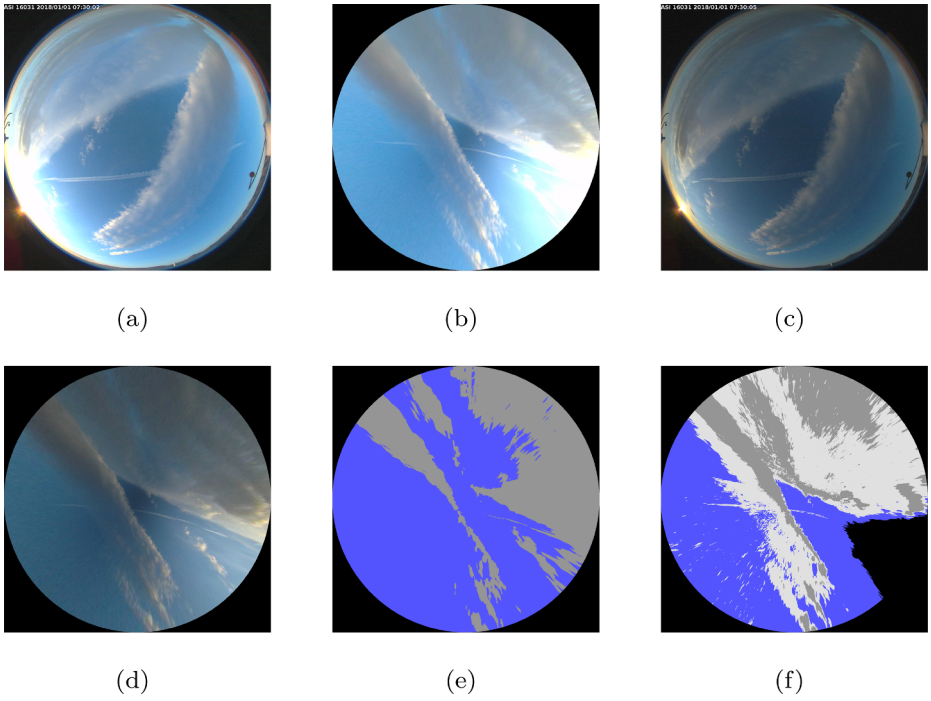



**Fig. 2.** NREL SRRL sky images and pre-processed images at the same time. (a) Original normal exposed image, (b) calibrated normal exposed image, (c) original underexposed image, (d) calibrated underexposed image, (e) BRBG-processed image, and (f) CDOC-processed image.

```
# specify directory to save files
root_data <- getwd()
# list files in the directory
list.files(root_data)

## character(0)

# download sky images and irradiance time series between the date range
date_start <- '2017-12-30'
date_end <- '2018-01-02'
SRRL.download(root_data, date_start, date_end, skyimg=T, tmseries=T, ifunzip=
T, ifunique=T)
# check downloaded files
list.files(root_data)

## [1] "20171230"                          "20171231"
## [3] "20180101"                          "20180102"
## [5] "SRRL_measurement_timeseries.csv"
```

A large collection of sky image features have been proven beneficial to very-short-term and short-term solar forecasting, including pixel RGB statistics (Yang et al., 2014), cloud motion vectors (Chow et al., 2011), and cloud coverage (Chu et al., 2013; Fu and Cheng, 2013). The `OpenSolar` package provides availability and flexibility of sky image pre-processing through the `SRRL.read()` function. Five critical features of raw sky images and CDOC-processed images are extracted, which are mean, standard deviation, the second-order entropy[8] of raw sky image pixel normalized red-blue ratios, along with thin cloud coverage, and opaque cloud coverage from CDOC-processed images. We encourage processing images with more advanced techniques, such as convolutional neural networks, to extract other information. Therefore, the raw images are loaded and stored in pixel arrays with pixel RGB values, if `returnRGB` is TRUE. The following code shows an example of pre-processed images at one timestamp:

[8] The second-order entropy, also known as Shannon's entropy, measures how much information contained in the image.

```
# specify directory to save files
root_data <- getwd()
# which image to process
timestamp <- '2018-01-01 12:00'
# define parameters and process the image
root_data <- 'your data directory'
list_read <- SRRL.read(timestamp, root_data, returnRGB=T, processraw=T, proce
ssadv=T)
# check the results
img_raw <- list_read[[1]]
dim(img_raw)

## [1] 1501 1501    3

raw_feature <- list_read[[2]]
raw_feature

## [1] -0.3028366  0.1775277 -3.8358866

img_adv <- list_read[[3]]
dim(img_adv)

## [1] 1501 1501    3

cloud_coverage <- list_read[[4]]
cloud_coverage

## [1] 0.2172586 0.0524676
```

## 4. Sheffield Solar – Microgen database

### 4.1. Overview

The Microgen Database (Microgen)[9] is a dataset managed by Sheffield Solar, University of Sheffield, which collects PV data from over 7000 locations across the United Kingdom (Sheffield Solar, 2016). The PV generation data is uploaded to the Microgen database by PV system owners, and thus has various lengths and temporal resolutions across the different locations. The dataset includes both residential and commercial PV installations between 0.7 kilowattpeak (kWp) and 69 kWp with different orientations and tilt angles (Taylor et al., 2015). Few PV power generation datasets with such a large spatial coverage are publicly available (especially residential PV), primarily because of privacy concerns. We believe that the Microgen dataset provides valuable opportunities for data-driven research in both the solar energy and power system domains. The Microgen dataset has been subjected to several QC methods, and erroneous data has been isolated and corrected by Sheffield Solar (Taylor et al., 2015).

### 4.2. Potential usage

The two advantages of Microgen are: (i) having a large spatial coverage and (ii) having behind-the-meter PV generation data, which have led to a wide range of publications on spatial solar energy analysis and distributed power system research. More specifically, the dataset's spatial coverage is beneficial to large-scale PV monitoring and characterization (Taylor et al., 2015; Colantuono et al., 2014), solar power spatial aggregation modeling (Lingfors and Widén, 2016), and spatial–temporal solar forecasting (Silva and Brito, 2018). Behind-the-meter PV generation data has been used for distributed energy storage operation optimization (Hassan et al., 2017), distributed energy storage financial and environmental benefit assessment (Jones et al., 2017), PV investment analysis (Leicester et al., 2016), and PV self-consumption evaluation (Leicester et al., 2016).

### 4.3. Data pre-processing

Sheffield Solar requires submitting a data request form to gain access to Microgen. Two CSV files will be sent by email once the data request is approved, containing time series data and metadata of a collection of PV generation locations. A subset of Microgen was obtained by the authors and is used in this paper for demonstration purposes. The subset includes 50 distributed PV systems in the Southeast UK, which is geospatially diverse for solar energy research. The obtained meta information consists of geospatial coordinates, elevation, azimuth, capacity, panel size, etc., which are shown in Fig. 3. It is observed that all the PV systems are residential, since the maximum capacity is 3.45 kWp. The 50 PV generation time series range from 2014-01-01 to 2014-12-31 with a 30-min resolution.

The cumulative generation time series data is stored in one column of the CSV file, which is a typical database structure. The other three columns, i.e., id, date, and time, are used to differentiate PV location, date, and time information, respectively. The `Microgen.read()` function in the `OpenSolar` package calculates 30-min PV generation based on the cumulative generation reading and structurizes the one-column values in a standard multi-column time series data frame, the code for which is:

[9] https://www.microgen-database.org.uk.

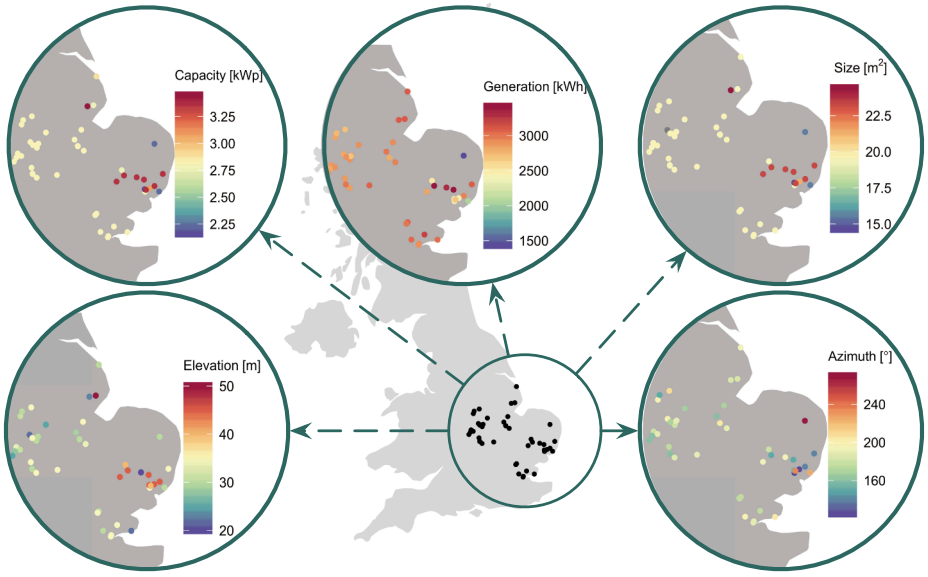



**Fig. 3.** Distribution map of PV locations of a microgen subset.

```
# specify data directory
root_data <- 'your data directory'
# read in Microgen data
data_microgen <- Microgen.read(root_data)
# check data dimension
dim(data_microgen)

## [1] 17520    52 # the first two columns are date and time
```

## 5. The Dataport database

### 5.1. Overview

The Dataport database is one of the largest datasets of disaggregated customer energy data, managed by Pecan Street Inc. Its data is collected from 1446 houses (1346 in Texas, 57 in Colorado, 58 in California, 4 in Oklahoma, and 1 in Illinois), of which 318 houses have PV installations (as of October 15th 2018). The dataset was originally created to understand customer behaviour regarding new devices, information, and price signals of the smart grid (Rhodes et al., 2014). The electricity consumption data of the entire home and various numbers of appliances is collected with less than or equal to 1-min resolution, along with natural gas and water consumption data. The Dataport dataset has a university schema, which offers all available data to researchers at US universities. The large number of monitored houses, high temporal resolution, and various behind-the-meter device (including behind-the-meter PVs) measurements make Dataport an ideal dataset for solar energy research.

### 5.2. Potential usage

Dataport has been extensively utilized in power system demand-side management (Bai et al., 2016), load forecasting (Tascikaraoglu and Sanandaji, 2016), electric vehicle integration (Shin and Baldick, 2017; Munshi and Mohamed, 2018), water/gas usage analysis and their nexus with electricity (Xue et al., 2017; Nagasawa et al., 2018; Vitter and Webber, 2018). It also contributes to solar energy research, such as distributed solar energy storage (Fares and Webber, 2017), solar-powered microgrid design (Halu et al., 2016; Lainfiesta et al., 2018), PV sizing (Kazhamiaka et al., 2018) and integration (Deetjen et al., 2017). However, it is surprising that this dataset has not yet been used for solar forecasting. We believe that Dataport is able to stimulate research in PV generation forecasting, especially spatial-temporal PV forecasting, behind-the-meter PV forecasting, net load forecasting, and PV forecasting benefit assessment.

### 5.3. Data pre-processing

There are three ways to approach the Dataport database: (i) via Spotlight, an Interactive Database Access tool, (ii) via the PostgreSQL client, and (iii) via outside client connections. Spotlight is able to export data by specifying the date range, table name, measured variables, and house IDs. Data is also accessible by any PostgreSQL client (e.g., pgAdmin) through SQL commands. Both approaches need to export and store data from other integrated development environments, which takes independent steps and extra effort. Two functions, namely, `Dataport.meta()` and `Dataport.get()`, are provided in the `OpenSolar` package to extract, download, filter, clean, and format data for PV-related research.

To fully take advantage of Dataport, table names and a list of houses with PV installations can be extracted through the `Dataport.meta()` function. In order to do that, the connection between R and the Dataport database is first set up with a PostgreSQL Database Interface. A username and a password are required to connect to Dataport, details of access to which can be found on the Dataport Advanced Access webpage.[10] The metadata can be downloaded if function parameter `metadownload` is TRUE and the saving directory is specified. An example of using the `Dataport.meta()` function is shown in the sample code below. There are a total of 72 tables in the Dataport database, which are useful for PV and PV-wind/load/electrical vehicle/energy storage/water/gas coordination research. The metadata includes a collection of information, such as state, city, PV installation capacity, and house size. It is important to note that the installation of a PV meter does not ensure the successful monitoring of PV generation (which will

[10] https://dataport.cloud.

result in NA elements in metadata and NA PV columns in the house measurement time series table/data frame). This issue will be tackled by metadata QC, which will be introduced in Section 5.4.

```
# specify the data directory
root_save <- getwd()
# specify function variables
usr <- 'your user name' #can be found on the Dataport Advanced Access webpage
psw <- 'your password' # once the registration request has been approved
metadownload <- T
QC <- F
# get the table names in Dataport database and PV meta data
list_result <- Dataport.meta(usr, psw, QC, metadownload, root_save)
table_list <- list_result[[1]]
data_meta <- list_result[[2]]
# check results
length(table_list)
## [1] 72
nrow(data_meta)
## [1] 318
```

The `Dataport.get()` function fetches behind-the-meter measurements of a house, once the `house_id` parameter is specified. The measurement time series has several time resolutions, i.e., 1 h, 15 min, and 1 min, which can be determined by the `time_resolution` parameter. The `Dataport.get()` function also has a QC option, which will be introduced in Section 5.4.

```
# specify function variables
usr <- 'your user name' #can be found on the Dataport Advanced Access webpage
psw <- 'your password' # once the registration request has been approved
house_id <- 8872
time_resolution <- 'hours' # three options: 'minutes', '15min', 'hours'
QC <- F
data_house <- Dataport.get(usr, psw, house_id, time_resolution, QC)
head(data_house)

##   dataid           localhour       use       air1         gen      grid
## 1   8872 2012-05-02 01:00:00 0.4432833 0.14096667 -0.01196667 0.4432833
## 2   8872 2012-05-02 02:00:00 0.3588167 0.12580000 -0.01211667 0.3588167
## 3   8872 2012-05-02 03:00:00 0.3662167 0.12598333 -0.01208333 0.3662167
## 4   8872 2012-05-02 04:00:00 0.3735333 0.12506667 -0.01203333 0.3735333
## 5   8872 2012-05-02 05:00:00 0.2743833 0.08768333 -0.01205000 0.2743833
## 6   8872 2012-05-02 06:00:00 0.1884500 0.00000000 -0.01436667 0.1884500
```

### 5.4. Quality control

QC of Dataport is performed by the `OpenSolar` package, which can be divided into metadata QC and time series QC. The metadata documents the PV installation information, which cannot guarantee the existence of measurements. To avoid empty PV columns returned by the `Dataport.get()` function, the right metadata should be properly quality-controlled. Since there is no additional information to identify the success of actual monitoring, PV value existence check is performed for all of the 318 PV installed houses by setting the `QC` parameter as TRUE. An example of quality controlled metadata extraction is shown in the following code segment. There are 190 out of 318 PV-installed houses having PV measurements. It is also important to note that checking through the electricity table in the database takes non-negligible computational time (around 116 min on a laptop with an Intel Core i7 2.6 GHz processor and a 16.0 GB RAM).

```
# setting up computational time calculation
begtime <- Sys.time()
# specify function variables
usr <- 'your user name' #can be found on the Dataport Advanced Access webpage
psw <- 'your password' # once the registration request has been approved
metadownload <- F
QC <- T
list_result <- Dataport.meta(usr, psw, QC, metadownload, root_save)
nrow(list_result[[2]])

## [1] 190

# print computational time
runtime <-  difftime(Sys.time(),begtime,tz, units = c( "mins"))
cat("Overall Computational time (mins):", runtime, "\n")

## Overall Computational time (mins): 115.7839
```

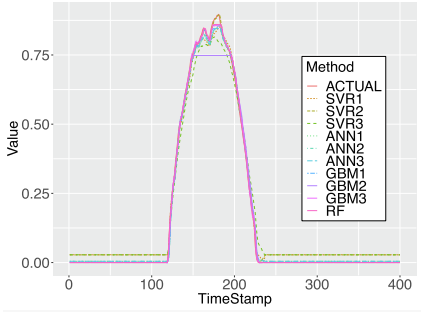
The measurements of Dataport are examined by several QC thresholds (the details are contained in the required non-disclousre agreement), during which spurious data are removed. In this case, four additional QC criteria are applied to (i) filter out discontinuous variables, which are defined as more than 10% values missing, (ii) restrict PV values between 0 and the rated capacity, (iii) linearly interpolate NA values, and (iv) identify deleted rows and perform linear interpolation. QC flags indicate good data by 0, missing data by 1, out-of-bound data by 2, and deleted data by 3. Extracting data with and without QC is shown as follows:

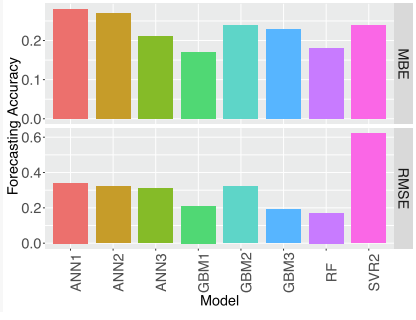
```
# specify function variables
usr <- 'your user name' #can be found on the Dataport Advanced Access webpage
psw <- 'your password' # once the registration request has been approved
house_id <- 8872
time_resolution <- '15min' # three options: 'minutes', '15min', 'hours'
QC <- T
data_unQC <- Dataport.get(usr, psw, house_id, time_resolution, QC)
nrow(data_unQC)
## [1] 38784
range(data_unQC$gen)
## [1] 0.000000 4.527467
QC <- F
data_QC <- Dataport.get(usr, psw, house_id, time_resolution, QC)
nrow(data_QC)
## [1] 38780
range(data_QC$gen)
## [1] -0.04346667  4.52746667
```

## 6. Benchmark modeling for short-term solar forecasting

Short-term solar forecasting plays an important role in power system operations. The `OpenSolar` package provides a function, `MLForecast()`, to mitigate the trivial benchmark modeling process in solar forecasting. A total of 10 powerful and widely-used machine-learning models are provided in the function, incuding 3 support vector regression (SVR) models, 3 artificial neural networks (ANNs), 3 gradient boosting machine (GBM) models, and a random forest (RF) model (Feng et al., 2017a). The training and forecasting process of these 10 models can be realized with just one line of code once the data is formatted and cleaned. In addition, forecasting time horizon and training/testing data partition ratio are required by the function. A matrix with both the forecast and actual time series, and a forecast evaluation metric table are generated. A visualization function, `MLVisual()`, is also provided to visualize the forecasting results. `MLVisual()` takes the forecast results generated by the `MLForecast()` function and outputs actual and forecast time series and barplots of three key forecast error metrics:

```
library(OpenSolar)
root_data <- 'your data directory'
SPDIS.download(root_data, list_st_download = 'Texas', ifunzip = T, actualonly = T)
## Download SPDIS State: Texas
list_data <- SPDIS.read(root_data, name_st = 'Texas', list_files, readall = T)
data_fmt <- list_data[[1]][1:5000,1:10]# test with a subset
list_forecasts <- MLForecast(data_fmt[,2:ncol(data_fmt)], 1, 2/3)
dim(list_forecasts[[1]])
## [1] 1666   11
dim(list_forecasts[[2]])
## [1] 10 11
plots <- MLVisual(list_forecasts[[1]], list_forecasts[[2]], 100, 400)
print(plots[1])
print(plots[2])
```



## 7. Conclusion and future work

In this paper, a package with both R and Python versions, `OpenSolar`, was developed to promote the openness and accessibility of solar data. Specifically, there are four publicly available datasets included in the package, namely, (i) NREL Solar Power Data for Integration Studies dataset, (ii) NREL Solar Radiation Research Laboratory dataset, (iii) Sheffield Solar-Microgen database, and (iv) Dataport database. The four datasets provide diverse types of solar research data, such as: behind-the-meter measurements, PV power, sky images, and meteorological variables. This paper has described how these datasets, their quality control, potential uses, and sample code scripts from the `OpenSolar` package can be used to download and preprocess the data. The `OpenSolar` package is expected to bridge the gap among the solar data science, power system research, and machine/deep learning domains, making different solar data types more readily available to both solar energy researchers and non-domain experts.

In the future, we will extend this research in the following directions: (i) including more datasets in the package, (ii) providing deep-learning-based example usage of the datasets, and (iii) setting up standard datasets and benchmarking models for data-driven modeling in solar energy.

## Appendix A. Example use case 1: temporal reconciliation with the Microgen dataset

Power systems require solar forecasts with various time resolutions. However, forecasting solar power independently with different time resolutions suffers from aggregate inconsistencies. Regression estimator-based reconciliation methods have been verified to preserve consistency in the solar forecasting temporal hiearchy and provide more accurate solar forecasts (Yang et al., 2017). In this appendix, we implement the temporal reconciliation methods proposed by Yang et al. (2017) and reproduce similar results as a Microgen dataset example use case. The case studies are included in the R script named `MicrogenExample.R`. Details of the temporal reconciliation methods can be found in Yang et al. (2017).

## Appendix B. Example use case 2: geographical reconciliation with the SPDIS dataset

Solar forecasting plays crucial roles in different geographical-level power system operations. For example, customer-level forecasts can be used for demand response, while system-level forecasts can be used for unit commitment and economic dispatch. Being provided by different vendors, inconsistencies also exist among solar forecasts with different geographical resolutions. Yang et al. (2017) regulated the inconsistent spatial-hierarchical solar forecasts by geographical reconciliation techniques. The SPDIS dataset is used to reproduce the empirical portion of Yang et al. (2017), which aims to reveal the potential usage of the solar data with a large geographical coverage. Results of the case studies can be generated by executing the R script named `SPDISExample.R`. Details of the geographical reconciliation methods can be found in Yang et al. (2017).

## Appendix C. OpenSolar Python library

The OpenSolar Python library (OpenSolar-Python) contains the same 5 functions with the identical input and output formats. The installation of the OpenSolar-Python can be conducted by pip, the Python package installer, from the Github.[11,12] The installation code is shown as:

```
pip install git+https://github.com/UTD-DOES/OpenSolar_Python
```

## Appendix D. Supplementary material

Supplementary data associated with this article can be found, in the online version, at https://doi.org/10.1016/j.solener.2019.07.016.

## References


Anderberg, Mary, Sengupta, Manajit, 2014. Comparison of data quality of NOAA's ISIS and SURFRAD networks to NREL's SRRL-BMS. Technical report, National Renewable Energy Lab. (NREL), Golden, CO (United States).

Augustine, John A., DeLuisi, John J., Long, Charles N., 2000. SURFRAD–A national surface radiation budget network for atmospheric research. Bull. Am. Meteorol. Soc. 81 (10), 2341–2358.

Bai, Yang, Zhong, Haiwang, Xia, Qing, 2016. Real-time demand response potential evaluation: a smart meter driven method. In: Power and Energy Society General Meeting (PESGM), 2016. IEEE, pp. 1–5.

Bloom, Aaron, Townsend, Aaron, Palchak, David, Novacheck, Joshua, King, Jack, Barrows, Clayton, Ibanez, Eduardo, O'Connell, Matthew, Jordan, Gary, Roberts, Billy, et al., 2016. Eastern renewable generation integration study. Technical report, National Renewable Energy Laboratory, Golden, CO, Tech. Rep. NREL/TP-6A20-64472.

Brower, Michael, et al., 2009. Development of Eastern regional wind resource and wind plant output datasets. Technical report, National Renewable Energy Laboratory, Golden, CO, Tech. Rep. No. NREL/SR-550-46764.

Chow, Chi Wai, Urquhart, Bryan, Lave, Matthew, Dominguez, Anthony, Kleissl, Jan, Shields, Janet, Washom, Byron, 2011. Intra-hour forecasting with a total sky imager at the UC San Diego solar energy testbed. Solar Energy 85 (11), 2881–2893.

Chu, Yinghao, Pedro, Hugo T.C., Coimbra, Carlos F.M., 2013. Hybrid intra-hour DNI forecasts with sky image processing enhanced by stochastic learning. Solar Energy 98, 592–603.

Colantuono, Giuseppe, Everard, Aldous, Hall, Lisa M.H., Buckley, Alastair R., 2014. Monitoring nationwide ensembles of PV generators: limitations and uncertainties. The case of the UK. Solar Energy 108, 252–263.

Cox, Sadie, Lopez, Anthony, Watson, Andrea, Grue, Nick, Leisch, Jennifer E., 2018. Renewable energy data, analysis, and decisions: a guide for practitioners. Technical report.

Deetjen, Thomas A., Vitter, J. Scott, Webber, Michael E., 2017. Improving solar-induced grid-level flexibility requirements using residential central utility plants. In: PowerTech, 2017 IEEE Manchester. IEEE, pp. 1–6.

Diagne, Maimouna, David, Mathieu, Boland, John, Schmutz, Nicolas, Lauret, Philippe, 2014. Post-processing of solar irradiance forecasts from WRF model at Reunion Island. Solar Energy 105, 99–108.

Dobos, Aron, 2014. PVWatts version 5 manual. Technical report, National Renewable Energy Laboratory Golden, CO.

Fares, Robert L., Webber, Michael E., 2017. The impacts of storing solar energy in the home to reduce reliance on the utility. Nature. Energy 2 (2), 17001.

Feng, Cong, Zhang, Jie, 2018. Hourly-similarity based solar forecasting using multi-model machine learning blending. In: IEEE PES General Meeting 2018. IEEE PES.

Feng, Cong, Cui, Mingjian, Hodge, Bri-Mathias, Zhang, Jie, 2017a. A data-driven multi-model methodology with deep feature selection for short-term wind forecasting. Appl. Energy 190, 1245–1257.

Feng, Cong, Cui, Mingjian, Lee, Meredith, Zhang, Jie, Hodge, Bri-Mathias, Lu, Siyuan, Hamann, Hendrik F., 2017b. Short-term global horizontal irradiance forecasting based on sky imaging and pattern recognition. In: IEEE PES General Meeting. IEEE.

Feng, Cong, Cui, Mingjian, Hodge, Bri-Mathias, Lu, Siyuan, Hamann, Hendrik, Zhang, Jie, 2018. Unsupervised clustering-based short-term solar forecasting. IEEE Trans. Sust. Energy.

Feng, Cong, Sun, Mucun, Cui, Mingjian, Chartan, Erol Kevin, Hodge, Bri-Mathias, Zhang, Jie, 2019. Characterizing forecastability of wind sites in the united states. Renew. Energy 133, 1352–1365.

Fu, Chia-Lin, Cheng, Hsu-Yung, 2013. Predicting solar irradiance with all-sky image features via regression. Solar Energy 97, 537–550.

GE Energy, 2010. Western wind and solar integration study. Technical report, Citeseer.

Ghonima, M.S., Urquhart, B., Chow, C.W., Shields, J.E., Cazorla, A., Kleissl, J., 2012. A method for cloud detection and opacity classification based on ground based sky imagery. Atmosph. Meas. Tech. 5 (11), 2881–2892.


[11] https://github.com/UTD-DOES/OpenSolar_Python

[12] https://zenodo.org/badge/latestdoi/173795145

Gueymard, Christian A., Wilcox, Stephen M., 2011. Assessment of spatial and temporal variability in the US solar resource from radiometric measurements and predictions from models using ground-based or satellite data. Solar Energy 85 (5), 1068–1084.
Habte, Aron, Sengupta, Manajit, Lopez, Anthony, 2017. Evaluation of the National Solar Radiation Database (NSRDB): 1998–2015. Technical Report, National Renewable Energy Lab. (NREL), Golden, CO (United States).
Halu, Arda, Scala, Antonio, Khiyami, Abdulaziz, González, Marta C., 2016. Data-driven modeling of solar-powered urban microgrids. Sci. Adv. 2 (1), e1500700.
Hassan, Abubakar Sani, Cipcigan, Liana, Jenkins, Nick, 2017. Optimal battery storage operation for PV systems with tariff incentives. Appl. Energy 203, 422–441.
Holmgren, William F., Andrews, Robert W., Lorenzo, Antonio T., Stein, Joshua S., 2015. PVLIB python 2015. In: 2015 IEEE 42nd Photovoltaic Specialist Conference (PVSC).
Jones, Christopher, Peshev, Vladimir, Gilbert, Paul, Mander, Sarah, 2017. Battery storage for post-incentive PV uptake? A financial and life cycle carbon assessment of a non-domestic building. J. Clean. Prod. 167, 447–458.
Kang, Byung O, Tam, Kwa-Sur, 2013. A new characterization and classification method for daily sky conditions based on ground-based solar irradiance measurement data. Solar Energy 94, 102–118.
Kazhamiaka, Fiodar, Ghiassi-Farrokhfal, Yashar, Keshav, Srinivasan, Rosenberg, Catherine, 2018. Robust and practical approaches for solar PV and storage sizing. In: Proceedings of the Ninth International Conference on Future Energy Systems. ACM, pp. 146–156.
Kleissl, Jan, 2013. Solar Energy Forecasting and Resource Assessment. Academic Press.
Kleissl, Jan, 2018. Special issue on progress. Solar Energy.
Lainfiesta, Maximiliano, Zhang, Xuewei, Sunday, Rick, 2018. Design of solar-powered microgrid at Texas A&M university-kingsville. In: Texas Power and Energy Conference (TPEC), 2018 IEEE. IEEE, pp. 1–6.
Lamigueiro, Oscar Perpinan, Almeida, Marcelo Pinho, Lamigueiro, Maintainer Oscar Perpinan, 2018. Meteoforecast: Numerical Weather Predictions. R package version 0.52. < https://cran.r-project.org/package=meteoForecast > .
Lave, Matthew, Kleissl, Jan, 2010. Solar variability of four sites across the state of Colorado. Renew. Energy 35 (12), 2867–2873.
Lave, Matthew, Kleissl, Jan, 2011. Optimum fixed orientations and benefits of tracking for capturing solar radiation in the continental United States. Renew. Energy 36 (3), 1145–1152.
Leicester, Philip A, Goodier, Chris I, Rowley, Paul, 2016. Probabilistic evaluation of solar photovoltaic systems using Bayesian networks: a discounted cash flow assessment. Prog. Photovolt.: Res. Appl. 24 (12), 1592–1605.
Leicester, Philip A., Goodier, Chris I., Rowley, Paul N., 2016. Probabilistic analysis of solar photovoltaic self-consumption using Bayesian network models. IET Renew. Power Gener. 10 (4), 448–455.
Lew, Debra, Brinkman, Greg, Ibanez, E., Hodge, B., King, J., 2013. The Western wind and solar integration study phase 2. Contract 303, 275–3000.
Lingfors, David, Widén, Joakim, 2016. Development and validation of a wide-area model of hourly aggregate solar power generation. Energy 102, 559–566.
Lu, Siyuan, Shao, Xiaoyan, Freitag, Marcus, Klein, Levente J., Renwick, Jason, Marianno, Fernando J., Albrecht, Conrad, Hamann, Hendrik F., 2016. IBM PAIRS curated big data service for accelerated geospatial data analytics and discovery. In: 2016 IEEE International Conference on Big Data (Big Data). IEEE, pp. 2672–2675.
Luiz, Eduardo Weide, Martins, Fernando Ramos, Costa, Rodrigo Santos, Pereira, Enio Bueno, 2018. Comparison of methodologies for cloud cover estimation in Brazil-A case study. Energy Sust. Dev. 43, 15–22.
Martinez-Anido, Carlo Brancucci, Botor, Benjamin, Florita, Anthony R., Draxl, Caroline, Lu, Siyuan, Hamann, Hendrik F., Hodge, Bri-Mathias, 2016. The value of day-ahead solar power forecasting improvement. Solar Energy 129, 192–203.
Maxwell, E., Wilcox, S., Rymes, M., 1993. Users manual for SERI QC software, assessing the quality of solar radiation data. Technical report, National Renewable Energy Lab. (NREL), Golden, CO (United States).
Miller, Nicholas W., Shao, M., Pajic, S., D'Aquila, R., 2014. Western wind and solar integration study phase 3–frequency response and transient stability. Technical report, National Renewable Energy Lab. (NREL), Golden, CO (United States); GE Energy Management, Schenectady, NY (United States).
AmrMunshi, Yasser A.-R.I.Mohamed, 2018. Unsupervised non-intrusive extraction of electrical vehicle charging load patterns. IEEE Trans. Ind. Inform.
Myers, Daryl R., 2012. Direct beam and hemispherical terrestrial solar spectral distributions derived from broadband hourly solar radiation data. Solar Energy 86 (9), 2771–2782.
Nagasawa, Kazunori, Rhodes, Joshua D., Webber, Michael E., 2018. Assessment of primary energy consumption, carbon dioxide emissions, and peak electric load for a residential fuel cell using empirical natural gas and electricity use profiles. Energy Build. 178, 242–253.
Ondraczek, Janosch, Komendantova, Nadejda, Patt, Anthony, 2015. WACC the dog: The effect of financing costs on the levelized cost of solar PV power. Renew. Energy 75, 888–898.
Pandžić, Hrvoje, Wang, Yishen, Qiu, Ting, Dvorkin, Yury, Kirschen, Daniel S., 2015. Near-optimal method for siting and sizing of distributed storage in a transmission network. IEEE Trans. Power Syst. 30 (5), 2288–2300.
Pecan Street Inc, 2019. Dataport Database. < https://dataport.cloud > .
Pfenninger, Stefan, DeCarolis, Joseph, Hirth, Lion, Quoilin, Sylvain, Staffell, Iain, 2017. The importance of open data and software: is energy research lagging behind? Energy Policy 101, 211–215.
Pfenninger, Stefan, Hirth, Lion, Schlecht, Ingmar, Schmid, Eva, Wiese, Frauke, Brown, Tom, Davis, Chris, Gidden, Matthew, Heinrichs, Heidi, Heuberger, Clara, et al., 2018. Opening the black box of energy modelling: strategies and lessons learned. Energy Strategy Rev. 19, 63–71.
Pohekar, S.D., Ramachandran, M., 2004. Application of multi-criteria decision making to sustainable energy planning-a review. Renew. Sust. Energy Rev. 8 (4), 365–381.
Reikard, Gordon, 2009. Predicting solar radiation at high resolutions: a comparison of time series forecasts. Solar Energy 83 (3), 342–349.
Rhodes, Joshua D., Upshaw, Charles R., Harris, Chioke B., Meehan, Colin M., Walling, David A., Navrátil, Paul A., Beck, Ariane L., Nagasawa, Kazunori, Fares, Robert L., Cole, Wesley J., et al., 2014. Experimental and data collection methods for a large-scale smart grid deployment: methods and first results. Energy 65, 462–471.
Saade, Elizabeth, Clough, David E., Weimer, Alan W., 2014. Use of image-based direct normal irradiance forecasts in the model predictive control of a solar-thermal reactor. J. Solar Energy Eng. 136 (1), 010905.
Saber, Ahmed Yousuf, Venayagamoorthy, Ganesh Kumar, 2010. Efficient utilization of renewable energy sources by gridable vehicles in cyber-physical energy systems. IEEE Syst. J. 4 (3), 285–294.
Saber, Ahmed Yousuf, Venayagamoorthy, Ganesh Kumar, 2011. Plug-in vehicles and renewable energy sources for cost and emission reductions. IEEE Trans. Ind. Electron. 58 (4), 1229–1238.
Sengupta, Manajit, Habte, Aron, Gueymard, Christian, Wilbert, Stefan, Renne, Dave, 2017. Best practices handbook for the collection and use of solar resource data for solar energy applications. Technical report, National Renewable Energy Lab. (NREL), Golden, CO (United States).
Sengupta, Manajit, Xie, Yu, Lopez, Anthony, Habte, Aron, Maclaurin, Galen, Shelby, James, 2018. The National Solar Radiation Data Base (NSRDB). Renew. Sust. Energy Rev. 89, 51–60.
Sheffield Solar, 2016. Microgen Database. Sheffield Solar-University of Sheffield. < http://www.microgen-database.org.uk > .
Shin, Hunyoung, Baldick, Ross, 2017. Plug-in electric vehicle to home (V2H) operation under a grid outage. IEEE Trans. Smart Grid 8 (4), 2032–2041.
Silva, R. Amaro, Brito, M.C., 2018. Impact of network layout and time resolution on spatio-temporal solar forecasting. Solar Energy 163, 329–337.
Stoffel, T., Andreas, A., 1981. NREL Solar Radiation Research Laboratory (SRRL): Baseline Measurement System (BMS); golden, colorado (data). Technical report, National Renewable Energy Lab. (NREL), Golden, CO (United States).
Su, Han-I, Gamal, Abbas El, 2013. Modeling and analysis of the role of energy storage for renewable integration: power balancing. IEEE Trans. Power Syst. 28 (4), 4109–4117.
Tascikaraoglu, Akin, Sanandaji, Borhan M., 2016. Short-term residential electric load forecasting: a compressive spatio-temporal approach. Energy Build. 111, 380–392.
Taylor, Jamie, Leloux, Jonathan, Everard, Aldous M., Briggs, Julian, Buckley, Alastair, 2015. Monitoring thousands of distributed PV systems in the UK: Energy production and performance. PVSAT-11, Leeds.
Tewari, Saurabh, Geyer, Charles J., Mohan, Ned, 2011. A statistical model for wind power forecast error and its application to the estimation of penalties in liberalized markets. IEEE Trans. Power Syst. 26 (4), 2031–2039.
Tu, Chunming, He, Xi, Shuai, Zhikang, Jiang, Fei, 2017. Big data issues in smart grid – a review. Renew. Sust. Energy Rev. 79, 1099–1107.
Vick, Brian D., Myers, Daryl R., Boyson, William E., 2012. Using direct normal irradiance models and utility electrical loading to assess benefit of a concentrating solar power plant. Solar Energy 86 (12), 3519–3530.
Vitter, Jeffrey Scott, Webber, M.E., 2018. A non-intrusive approach for classifying residential water events using coincident electricity data. Environ. Model. Software 100, 302–313.
Xie, Yu, Sengupta, Manajit, Dooraghi, Mike, 2018. Assessment of uncertainty in the numerical simulation of solar irradiance over inclined PV panels: new algorithms using measurements and modeling tools. Solar Energy 165, 55–64.
Xue, Peng, Hong, Tianzhen, Dong, Bing, Mak, Cheukming, 2017. A preliminary investigation of water usage behavior in single-family homes. In: Building Simulation, vol. 10. Springer, pp. 949–962.
Yang, Dazhi, 2018. Solardata: an R package for easy access of publicly available solar datasets. Solar Energy.
Yang, Dazhi, Dong, Zibo, 2018. Operational photovoltaics power forecasting using seasonal time series ensemble. Solar Energy 166, 529–541.
Yang, Dazhi, Quan, Hao, Disfani, Vahid R., Liu, Licheng, 2017. Reconciling solar forecasts: geographical hierarchy. Solar Energy 146, 276–286.
Yang, Dazhi, Quan, Hao, Disfani, Vahid R., Carlos, D., Rodriguez-Gallegos, Carlos D., 2017. Reconciling solar forecasts: Temporal hierarchy. Solar Energy 158, 332–346.
Yang, Dazhi, Gueymard, Christian, Kleissl, Jan, 2018. Editorial: submission of data article is now open. Solar Energy.
Yang, Handa, Kurtz, Ben, Nguyen, Dung, Urquhart, Bryan, Chow, Chi Wai, Ghonima, Mohamed, Kleissl, Jan, 2014. Solar irradiance forecasting using a ground-based sky imager developed at UC San Diego. Solar Energy 103, 502–524.
Zell, Erica, Gasim, Sami, Wilcox, Stephen, Katamoura, Suzan, Stoffel, Thomas, Shibli, Husain, Engel-Cox, Jill, Subie, Madi Al, 2015. Assessment of solar radiation resources in Saudi Arabia. Solar Energy 119, 422–438.
Zhang, Jie, Hodge, Bri-Mathias, Florita, Anthony, 2013. Investigating the correlation between wind and solar power forecast errors in the western interconnection. In: ASME 2013 7th International Conference on Energy Sustainability collocated with the ASME 2013 Heat Transfer Summer Conference and the ASME 2013 11th International Conference on Fuel Cell Science, Engineering and Technology, American Society of Mechanical Engineers. pp. V001T16A003–V001T16A003.
Zhang, Jie, Hodge, Bri-Mathias, Florita, Anthony, 2014. Joint probability distribution and correlation analysis of wind and solar power forecast errors in the western interconnection. J. Energy Eng. 141 (1), B4014008.
Zhang, Jie, Florita, Anthony, Hodge, Bri-Mathias, Lu, Siyuan, Hamann, Hendrik F., Banunarayanan, Venkat, Brockway, Anna M., 2015. A suite of metrics for assessing the performance of solar power forecasting. Solar Energy 111, 157–175.
Zhen, Zhao, Wang, Fei, Sun, Yujing, Mi, Zengqiang, Liu, Chun, Wang, Bo, Lu, Jing, 2015. SVM based cloud classification model using total sky images for PV power forecasting. In: 2015 IEEE Power & Energy Society Innovative Smart Grid Technologies Conference (ISGT). IEEE, pp. 1–5.
Zhou, Kaile, Chao, Fu., Yang, Shanlin, 2016. Big data driven smart energy management: from big data to big insights. Renew. Sust. Energy Rev. 56, 215–225.