PVLib_Libya_Ghadames

February 23, 2019

https://pvlib-python.readthedocs.io/en/latest/forecasts.html

pvlib-python provides a set of functions and classes that make it easy to obtain weather forecast data and convert that data into a PV power forecast. Users can retrieve standardized weather forecast data relevant to PV power modeling from NOAA/NCEP/NWS models including the GFS, NAM, RAP, HRRR, and the NDFD. A PV power forecast can then be obtained using the weather data as inputs to the comprehensive modeling capabilities of PVLIB-Python. Standardized, open source, reference implementations of forecast methods using publicly available data may help advance the state-of-the-art of solar power forecasting.

pvlib-python uses Unidata's Siphon library to simplify access to real-time forecast data hosted on the Unidata THREDDS catalog. Siphon is great for programatic access of THREDDS data, but we also recommend using tools such as Panoply to easily browse the catalog and become more familiar with its contents.

We do not know of a similarly easy way to access archives of forecast data.

This document demonstrates how to use pvlib-python to create a PV power forecast using these tools. The forecast and forecast_to_power Jupyter notebooks provide additional example code.

https://anaconda.org/conda-forge/siphon

A collection of Python utilities for accessing remote geoscience data

conda install -c conda-forge siphon

conda install -c conda-forge/label/cf201901 siphon

https://anaconda.org/pvlib/pvlib

conda install -c pvlib pvlib // or https://pvlib-python.readthedocs.io/en/latest/installation.html

Description

PVLIB Python is a community supported tool that provides a set of functions and classes for simulating the performance of photovoltaic energy systems. PVLIB Python was originally ported from the PVLIB MATLAB toolbox developed at Sandia National Laboratories and it implements many of the models and methods developed at the Labs. More information on Sandia Labs PV performance modeling programs can be found at https://pvpmc.sandia.gov/. We collaborate with the PVLIB MATLAB project, but operate independently of it.

We need your help to make pvlib-python a great tool!

Documentation: http://pvlib-python.readthedocs.io

Source code: https://github.com/pvlib/pvlib-python

```
In [1]: import pandas as pd

        import matplotlib.pyplot as plt
```

```
import datetime

import siphon
```

```
In [2]: #import pvlib forecast models
        # from pvlib.forecast  import GFS, NAM, NDFD, HRRR, RAP
        from pvlib.forecast  import GFS
```

```
C:\Users\Mhdella\Anaconda3\lib\site-packages\pvlib\forecast.py:21: UserWarning: The forecast mo
  'The API may change, the functionality may be consolidated into an io ' +
```

Fore example: Sapporo City in Hokkaido, Japan
43.0621ř N, 141.3544ř E

1 Caculate the mean of the coordination of PV systems in Hokkaido

From file: LD_DETAIL_EN_excel.docx
Data 1: Targeted Solar Power Plants
S1: lat=42.7169, lng=141.6920625
S2: lat=43.12896, lng=144.1081429
mean(S1,S2):lat=42.90919333, lng=142.8195667
Data2: Measurement Locations (Temperature and Global Solar Radiation Values)
S1: lat=42.8769, lng=141.54755
S2: lat=43.3968, lng=144.15215
mean(S1,S2):lat=43.136825, lng=142.84985

```
In [3]: # specify location (Tucson, AZ)
        # latitude, longitude, tz = 32.2, -110.9, 'US/Arizona'


        ####### Hokkaido Location S1 Measurements
        # latitude, longitude, tz = 42.88, 141.55, 'Japan'
        # latitude, longitude, tz = 42.72, 141.69, 'Japan'

        # ##### Misurata Libya
        # latitude, longitude, tz = 32.3256, 15.0993, 'Libya'

        ##### Ghadames Libya
        latitude, longitude, tz = 30.1318, 9.4951, 'Libya'
```

```
In [4]: # specify time range.
        start = pd.Timestamp(datetime.date.today(), tz=tz)

        end = start + pd.Timedelta(days=7)

        irrad_vars = ['ghi', 'dni', 'dhi']
```

```
        print(start, end)
        tz
```

```
2019-02-23 00:00:00+02:00 2019-03-02 00:00:00+02:00
```

```
Out[4]: 'Libya'
```

Different dates from the past with Japan time zone
https://stackoverflow.com/questions/17159207/change-timezone-of-date-time-column-in-pandas-and-add-as-hierarchical-index

```
In [5]: # start=pd.Timestamp(2018, 12, 1, 12)
        start=pd.Timestamp(2019, 1, 23, 12)
        start=start.tz_localize('UTC').tz_convert(tz)

        # end=pd.Timestamp(2018, 12, 31, 12)
        # end=end.tz_localize('UTC').tz_convert(tz)

        end = start + pd.Timedelta(days=7)

        irrad_vars = ['ghi', 'dni', 'dhi']

        print(start, end)
        tz
```

```
2019-01-23 14:00:00+02:00 2019-01-30 14:00:00+02:00
```

```
Out[5]: 'Libya'
```

Next, we instantiate a GFS model object and get the forecast data from Unidata.

It will be useful to process this data before using it with pvlib. For example, the column names are non-standard, the temperature is in Kelvin, the wind speed is broken into east/west and north/south components, and most importantly, most of the irradiance data is missing. The forecast module provides a number of methods to fix these problems.

```
In [6]: model = GFS()
        data = model.get_processed_data(latitude, longitude, start, end)

        print(data.head())
```

```
                            temp_air  wind_speed         ghi         dni  \
2019-01-24 03:00:00+02:00   9.316498   11.128860    0.000000    0.000000
2019-01-24 06:00:00+02:00   8.612366   11.341315    0.000000    0.000000
2019-01-24 09:00:00+02:00  16.170044   14.057465   69.401412  163.391509
2019-01-24 12:00:00+02:00  23.540833   15.640877  578.062215  808.162001
2019-01-24 15:00:00+02:00  20.093536   14.900990  591.695612  811.599895
```

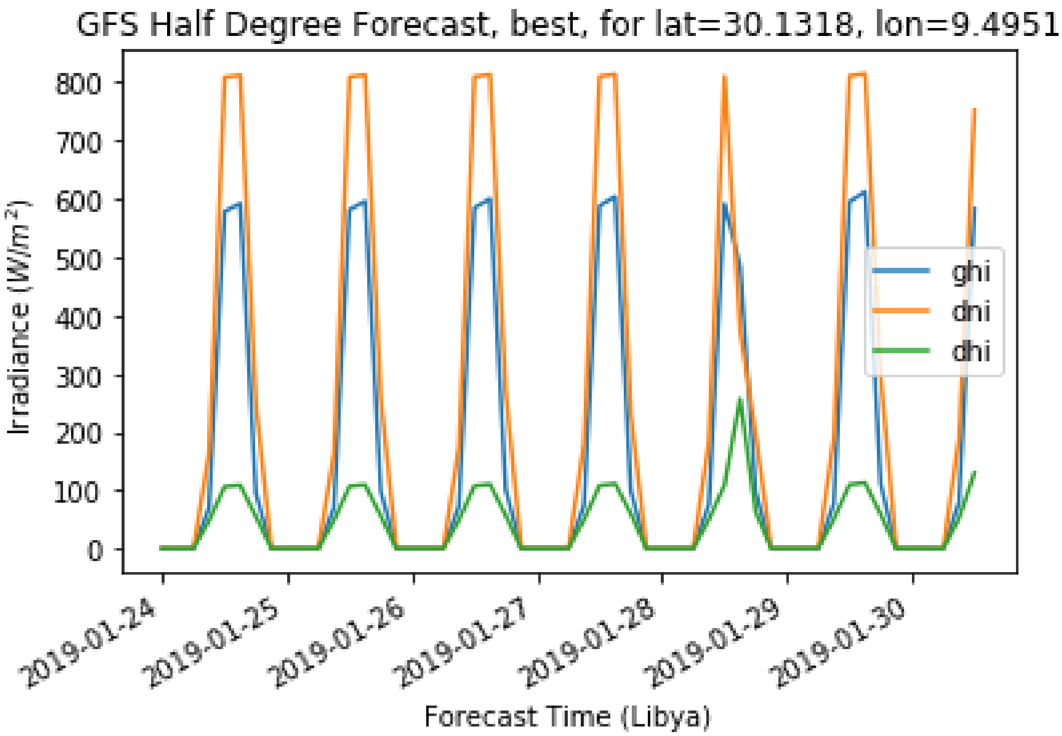
```
                                  dhi  total_clouds  low_clouds  mid_clouds  \
2019-01-24 03:00:00+02:00    0.000000           0.0         0.0         0.0
2019-01-24 06:00:00+02:00    0.000000           0.0         0.0         0.0
2019-01-24 09:00:00+02:00   47.554499           0.0         0.0         0.0
2019-01-24 12:00:00+02:00  106.451970           0.0         0.0         0.0
2019-01-24 15:00:00+02:00  108.847521           0.0         0.0         0.0

                           high_clouds
2019-01-24 03:00:00+02:00          0.0
2019-01-24 06:00:00+02:00          0.0
2019-01-24 09:00:00+02:00          0.0
2019-01-24 12:00:00+02:00          0.0
2019-01-24 15:00:00+02:00          0.0
```

Plot the outputs of forecast models, such as solar irradiance components, clouds, etc. (They are useful for solar power forecast).

For example GFS, a global mode:

The Global Forecast System (GFS) is the US model that provides forecasts for the entire globe. The GFS is updated every 6 hours. The GFS is run at two resolutions, 0.25 deg and 0.5 deg, and is available with 3 hour time resolution. Forecasts from GFS model were shown above. Use the GFS, among others, if you want forecasts for 1-7 days or if you want forecasts for anywhere on Earth.

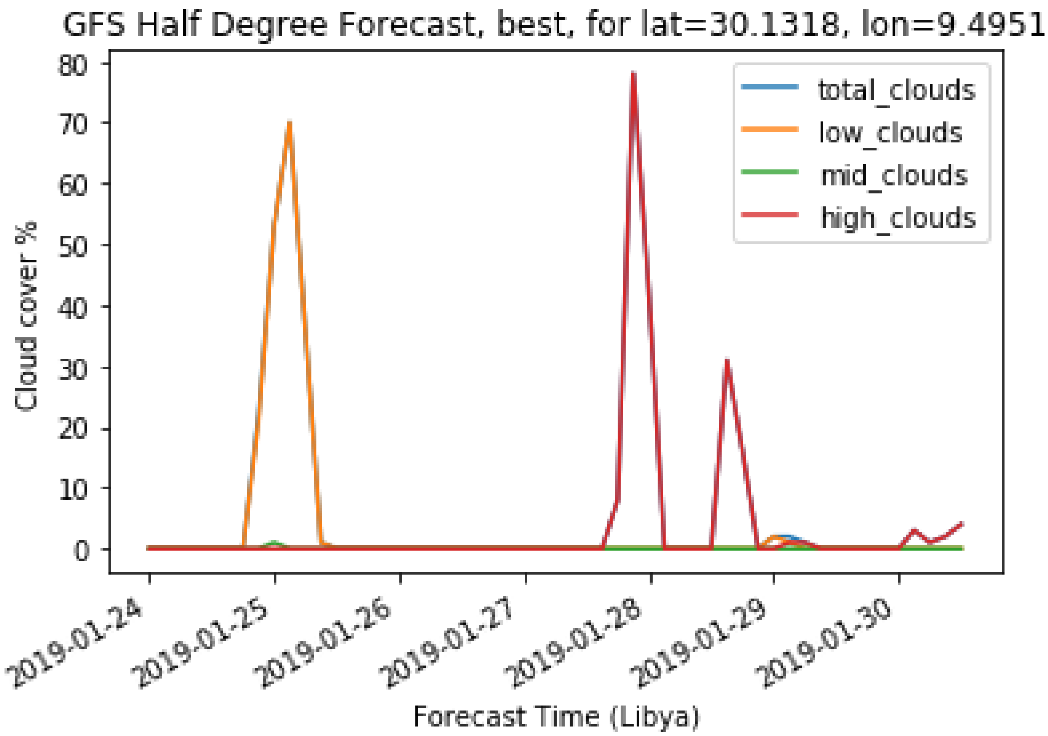
```
In [7]: # In [50]: model = HRRR()
        # data = model.get_processed_data(latitude, longitude, start, end)
        model = GFS()
        data[irrad_vars].plot();

        plt.ylabel('Irradiance ($W/m^2$)');
        plt.xlabel('Forecast Time ({})'.format(tz));
        plt.title('{}, for lat={}, lon={}'.format(model, latitude, longitude));
        plt.legend();
```



2 Cloud cover and radiation

All of the weather models currently accessible by pvlib include one or more cloud cover forecasts. For example, below we plot the GFS cloud cover forecasts

In [8]:
```
# plot cloud cover percentages
cloud_vars = ['total_clouds', 'low_clouds','mid_clouds', 'high_clouds']
data[cloud_vars].plot();
plt.ylabel('Cloud cover %');
plt.xlabel('Forecast Time ({})'.format(tz));
plt.title('{}, for lat={}, lon={}'.format(model, latitude, longitude));
plt.legend();
```



3 Extract solar radiation from cloud cover infromataion:

However, many of forecast models do not include radiation components in their output fields, or if they do then the radiation fields suffer from poor solar position or radiative transfer algorithms. It is often more accurate to create empirically derived radiation forecasts from the weather models' cloud cover forecasts.

PVLIB-Python provides two basic ways to convert cloud cover forecasts to irradiance forecasts. One method assumes a linear relationship between cloud cover and GHI, applies the scaling to a clear sky climatology, and then uses the DISC model to calculate DNI. The second method assumes a linear relationship between cloud cover and atmospheric transmittance, and then uses the Liu-Jordan [Liu60] model to calculate GHI, DNI, and DHI.

Note: these algorithms are not rigorously verified! The purpose of the forecast module is to provide a few exceedingly simple options for users to play with before they develop their own models. We strongly encourage pvlib users first read the source code and second to implement new cloud cover to irradiance algorithms.

The essential parts of the clear sky scaling algorithm are as follows. Clear sky scaling of climatological GHI is also used in Larson et. al. [Lar16].

```
In [9]: #### model.cloud_cover_to_irradiance
        # solpos = location.get_solarposition(cloud_cover.index)
        # cs = location.get_clearsky(cloud_cover.index, model='ineichen')
        # # offset and cloud cover in decimal units here
```

```
# # larson et. al. use offset = 0.35
# ghi = (offset + (1 - offset) * (1 - cloud_cover)) * ghi_clear
# dni = disc(ghi, solpos['zenith'], cloud_cover.index)['dni']
# dhi = ghi - dni * np.cos(np.radians(solpos['zenith']))
```

```
In [10]: import os
         import itertools
         import matplotlib.pyplot as plt
         import pandas as pd
         import pvlib
         from pvlib import clearsky, atmosphere, solarposition
         from pvlib.location import Location
         # from pvlib.iotools import read_tmy3
```

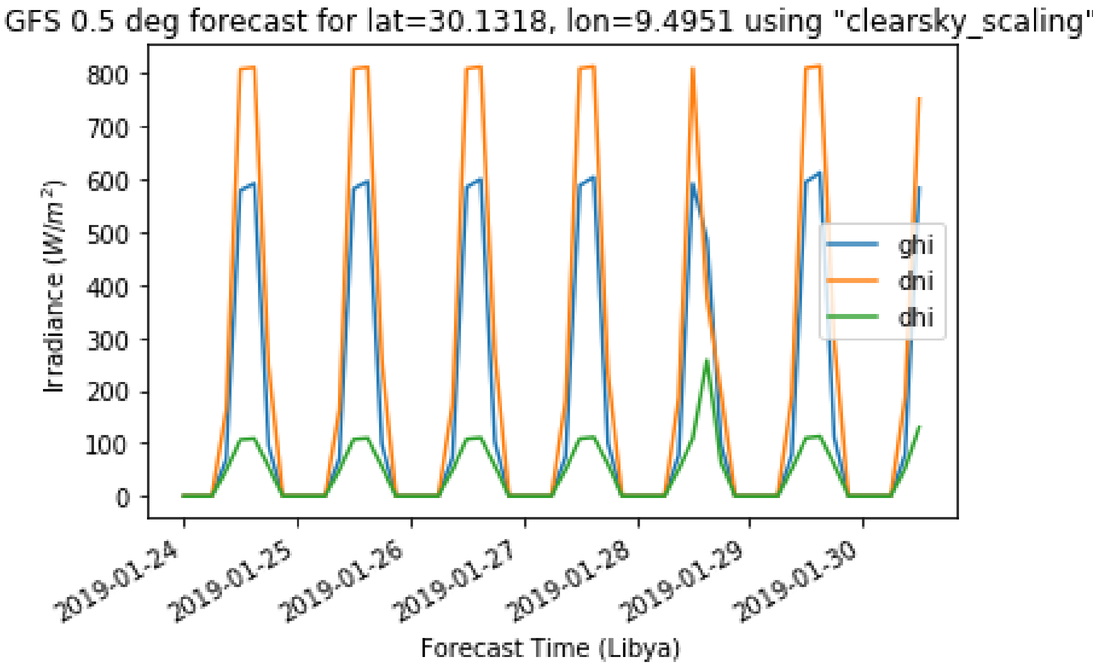
```
In [11]: # location = Location(latitude, longitude, tz, 700, 'Japan')
         # # location=Location(32.2, -111, 'US/Arizona', 700, 'Tucson')
         # # times = pd.DatetimeIndex(start='2016-12-01', end='2018-12-04', freq='1min', tz=lo
         # times = pd.DatetimeIndex(start='2016-07-01', end='2016-07-04', freq='1min', tz=loca

         # cs = location.get_clearsky(times)  # ineichen with climatology table by default
         # # cs.describe()
```

```
In [12]: # cs.plot();
         # # plt.ylabel('Irradiance $W/m^2$');
         # # plt.title('Ineichen, climatological turbidity');
```

```
In [13]: raw_data = model.get_data(latitude, longitude, start, end)
         # plot irradiance data
         data = model.rename(raw_data)
         irrads = model.cloud_cover_to_irradiance(data['total_clouds'], how='clearsky_scaling')
```

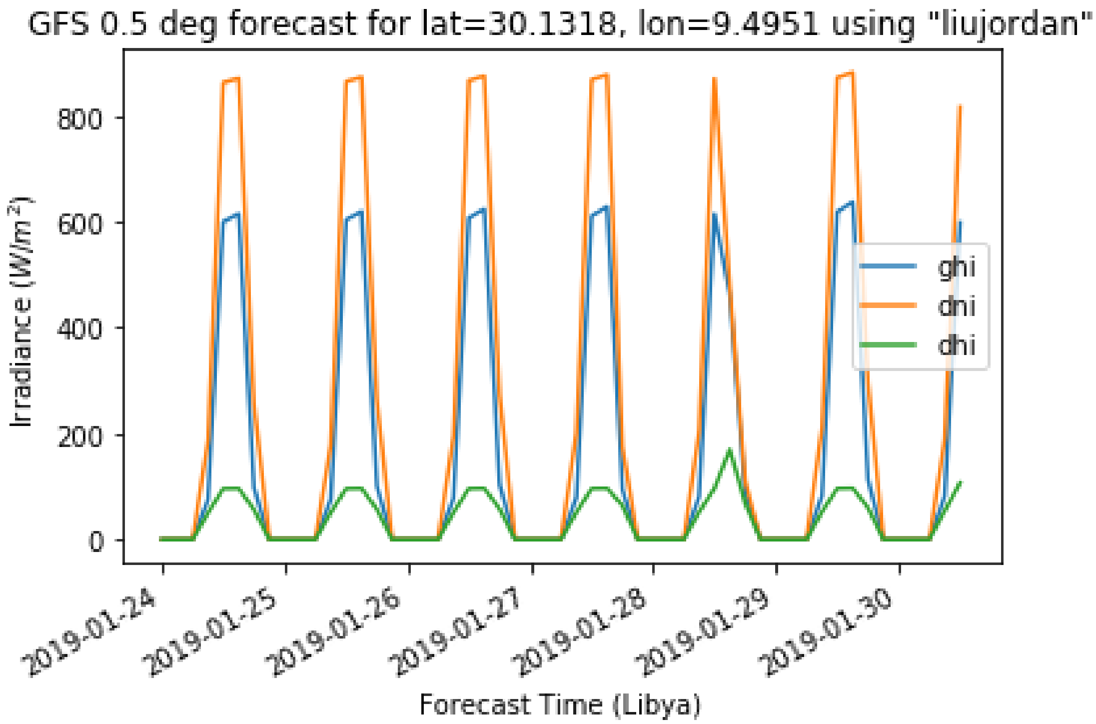
The figure below shows the result of the total cloud cover to irradiance conversion using the clear sky scaling algorithm

```
In [14]: irrads.plot();
         plt.ylabel('Irradiance ($W/m^2$)');
         plt.xlabel('Forecast Time ({})'.format(tz));
         plt.title('GFS 0.5 deg forecast for lat={}, lon={} using "clearsky_scaling"'.format(la

         plt.legend();
```



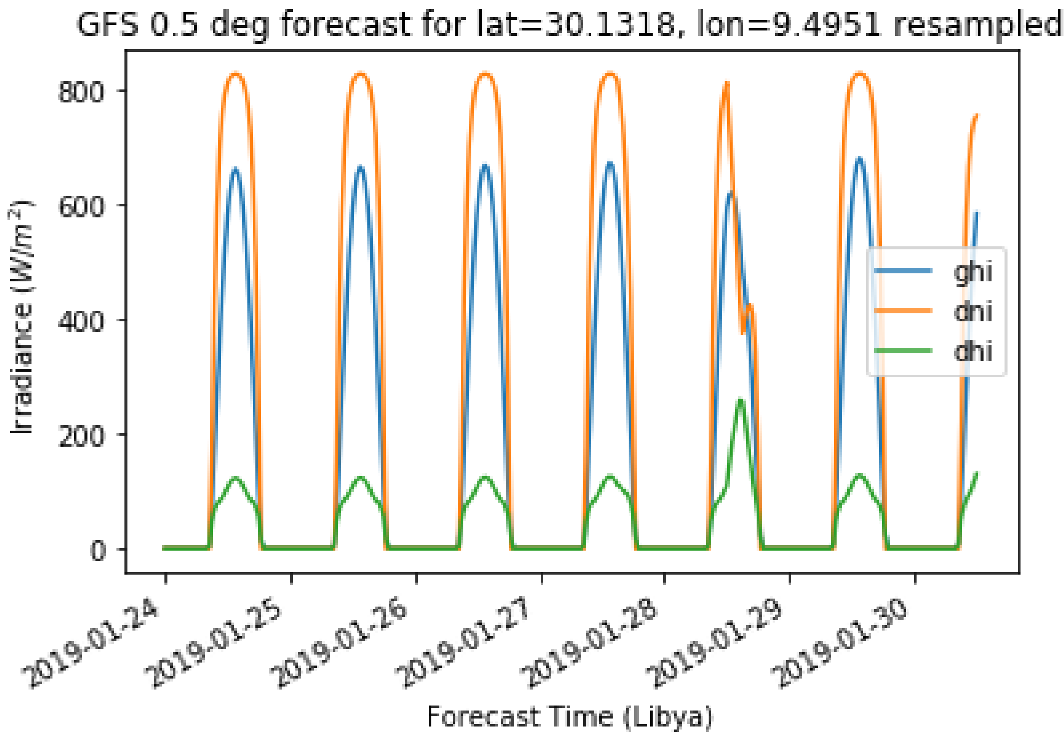
The essential parts of the Liu-Jordan cloud cover to irradiance algorithm are as follows.
The figure below shows the result of the Liu-Jordan total cloud cover to irradiance conversion.

```
In [15]: # plot irradiance data
         irrads = model.cloud_cover_to_irradiance(data['total_clouds'], how='liujordan')

         irrads.plot();

         plt.ylabel('Irradiance ($W/m^2$)');

         plt.xlabel('Forecast Time ({})'.format(tz));

         plt.title('GFS 0.5 deg forecast for lat={}, lon={} using "liujordan"'.format(latitude

         plt.legend();
```



Most weather model output has a fairly coarse time resolution, at least an hour. The irradiance forecasts have the same time resolution as the weather data. However, it is straightforward to interpolate the cloud cover forecasts onto a higher resolution time domain, and then recalculate the irradiance

In [16]:
```
# resampled_data = data.resample('5min').interpolate()
resampled_data = data.resample('30min').interpolate()

resampled_irrads = model.cloud_cover_to_irradiance(resampled_data['total_clouds'], how
resampled_irrads.plot();
plt.ylabel('Irradiance ($W/m^2$)');
plt.xlabel('Forecast Time ({})'.format(tz));
plt.title('GFS 0.5 deg forecast for lat={}, lon={} resampled'.format(latitude, longitu
plt.legend();
```



Users may then recombine resampled_irrads and resampled_data using slicing pandas.concat() or pandas.DataFrame.join().

We reiterate that the open source code enables users to customize the model processing to their liking.

[Lar16] Larson et. al. "Day-ahead forecasting of solar power output from photovoltaic plants in the American Southwest" Renewable Energy 91, 11-20 (2016).

[Liu60] B. Y. Liu and R. C. Jordan, The interrelationship and characteristic distribution of direct, diffuse, and total solar radiation, Solar Energy 4, 1 (1960).

4 PV Power Forecast

Finally, we demonstrate the application of the weather forecast data to a PV power forecast. Please see the remainder of the pvlib documentation for details.

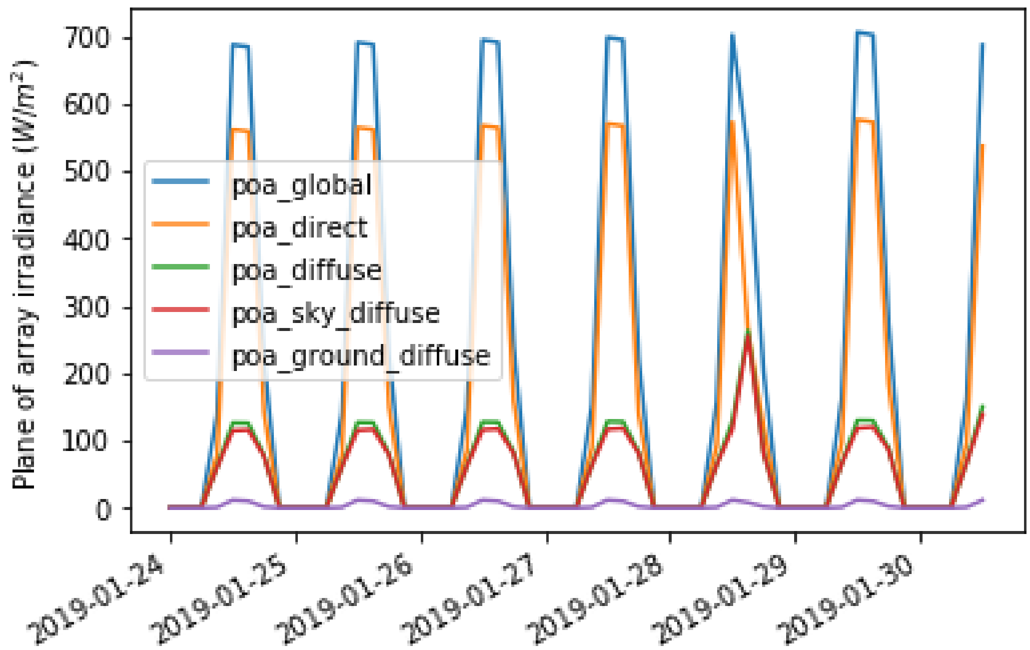
```
In [17]: from pvlib.pvsystem import PVSystem, retrieve_sam

         from pvlib.tracking import SingleAxisTracker

         from pvlib.modelchain import ModelChain

         sandia_modules = retrieve_sam('sandiamod')

         cec_inverters = retrieve_sam('cecinverter')
```

```
module = sandia_modules['Canadian_Solar_CS5P_220M___2009_']

inverter = cec_inverters['SMA_America__SC630CP_US_315V__CEC_2012_']

# model a big tracker for more fun
system = SingleAxisTracker(module_parameters=module,inverter_parameters=inverter,
                           modules_per_string=15,strings_per_inverter=300)
```

In [18]:
```
# fx is a common abbreviation for forecast
fx_model = GFS()
fx_data = fx_model.get_processed_data(latitude, longitude, start, end)

# use a ModelChain object to calculate modeling intermediates
mc = ModelChain(system, fx_model.location)

# extract relevant data for model chain
mc.run_model(fx_data.index, weather=fx_data);
```

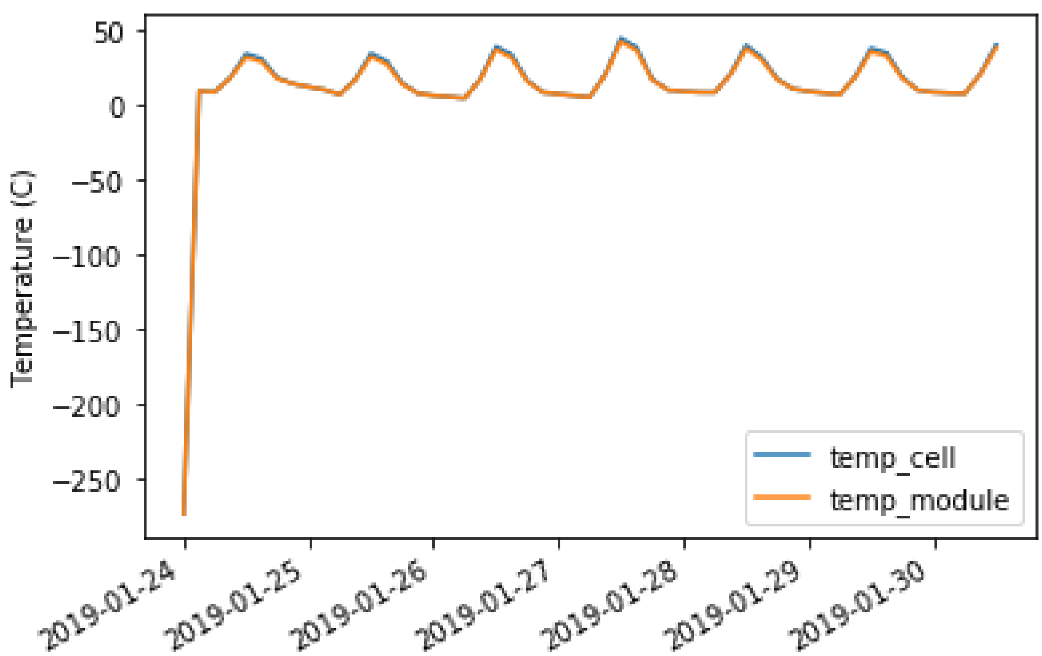
```
C:\Users\Mhdella\Anaconda3\lib\site-packages\pvlib\tracking.py:424: RuntimeWarning: invalid val
  temp = np.minimum(axes_distance*cosd(wid), 1)
C:\Users\Mhdella\Anaconda3\lib\site-packages\pvlib\tracking.py:431: RuntimeWarning: invalid val
  tracker_theta = np.where(wid < 0, wid + wc, wid - wc)
C:\Users\Mhdella\Anaconda3\lib\site-packages\pvlib\tracking.py:435: RuntimeWarning: invalid val
  tracker_theta[tracker_theta > max_angle] = max_angle
C:\Users\Mhdella\Anaconda3\lib\site-packages\pvlib\tracking.py:436: RuntimeWarning: invalid val
  tracker_theta[tracker_theta < -max_angle] = -max_angle
C:\Users\Mhdella\Anaconda3\lib\site-packages\pvlib\tracking.py:543: RuntimeWarning: invalid val
  surface_azimuth[surface_azimuth < 0] += 360
C:\Users\Mhdella\Anaconda3\lib\site-packages\pvlib\tracking.py:544: RuntimeWarning: invalid val
  surface_azimuth[surface_azimuth >= 360] -= 360
C:\Users\Mhdella\Anaconda3\lib\site-packages\pvlib\pvsystem.py:1917: RuntimeWarning: invalid va
  spectral_loss = np.maximum(0, np.polyval(am_coeff, airmass_absolute))
C:\Users\Mhdella\Anaconda3\lib\site-packages\pvlib\pvsystem.py:1773: RuntimeWarning: invalid va
  Bvoco*(temp_cell - T0)))
C:\Users\Mhdella\Anaconda3\lib\site-packages\pvlib\pvsystem.py:1779: RuntimeWarning: invalid va
  Bvmpo*(temp_cell - T0)))
C:\Users\Mhdella\Anaconda3\lib\site-packages\pvlib\pvsystem.py:2551: RuntimeWarning: invalid va
  ac_power = np.minimum(Paco, ac_power)
```

In [19]:
```
mc.total_irrad.plot();
plt.ylabel('Plane of array irradiance ($W/m^2$)');

plt.legend(loc='best');
```



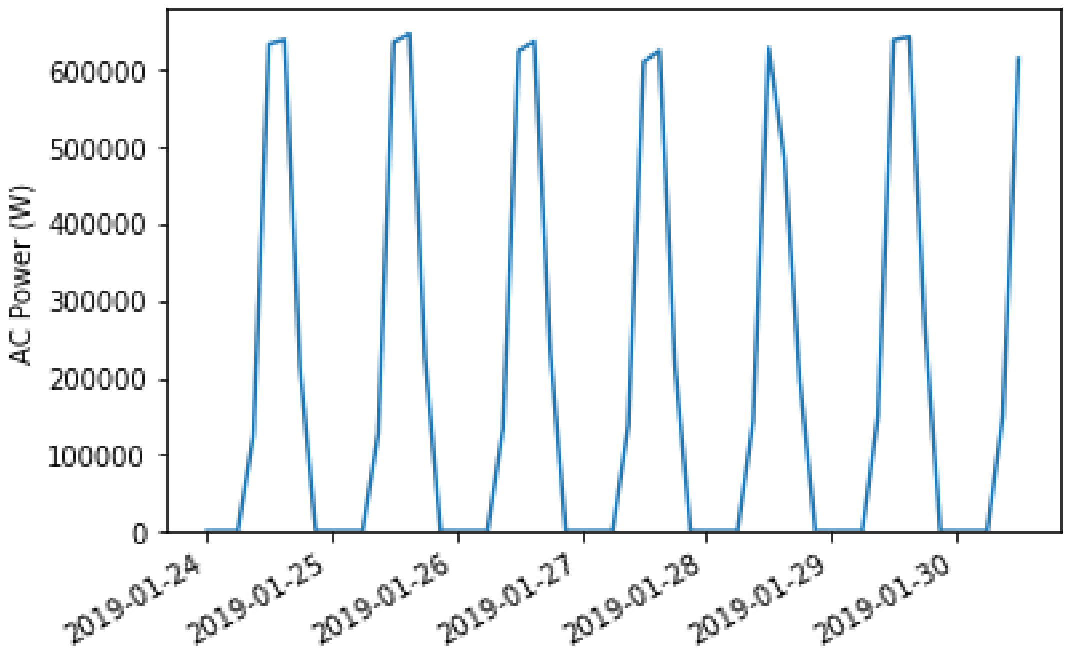
…the cell and module temperature…

```
In [20]: mc.temps.plot();
         plt.ylabel('Temperature (C)');
```



…and finally AC power…

```
In [21]: mc.ac.fillna(0).plot();

         plt.ylim(0, None);

         plt.ylabel('AC Power (W)');
```




```
In [22]: mc.ac.fillna(0).describe()

Out[22]: count        53.000000
         mean     196209.938688
         std      257304.682776
         min           0.000000
         25%           0.000000
         50%           0.000000
         75%      268547.609098
         max      648111.949666
         dtype: float64

In [ ]:
```