What kinds of renewable energy forecasts?

**Technology**
- Solar
- PV
- CSP
- Wind
- Biofuels
- Geothermal
- Tidal
- Hydro

**Time horizon**
- 1 minute
- 1 hour
- 1 day
- 1 week
- 1 month
- 1 season
- 1 year
- 1 investment

**Time resolution**
- 1 minute
- 1 hour
- 1 day
- 1 week
- 1 month
- 1 season
- 1 year
- 1 investment

**Data source**
- Observational
  - Weather
  - Satellites
  - RADAR
  - Sky cameras
  - LIDAR
- Modeled
  - Weather
  - Climate
  - Satellite
  - RADAR

ARIZONA Hydrology and Atmospheric Sciences
Solar and wind price forecasts

Inputs:
- Price data
- Tariffs
- Innovation rate
- Subsidies (local, state, federal, foreign)
- Regulatory models
- Economic models

Margolis et al., NREL/Sunshot 2017
NREL/PR-6A20-68425
Solar and wind price forecasts

Inputs:
- Price data
- Tariffs
- Innovation rate (wind and gas)
- Subsidies (local, state, federal, foreign)
- Regulatory models
- Economic models

Figure 8. Projected costs for the SMART wind power plant at a range of different wind resource sites using the accelerated R&D pathway relative to future natural gas prices

Dykes et. al., NREL 2017
Solar and wind capacity forecasts

EIA Annual Energy Outlook 2017
eia.gov

Wind x 2.5?
Solar PV x 100!
Solar Thermal and Offshore Wind flat

Source: U.S. Energy Information Administration
Solar and wind capacity forecasts

“America's Renewable Electricity Forecast Grows To 2050, Even Under Trump”

Solar and wind yearly generation forecasts

Source: Bloomberg New Energy Finance, New Energy Outlook 2017
Solar and wind resource assessments

Inputs:
- Weather observations
- Satellite observations
- Weather models
- Weather to power models
Temperature

Dew point

Global Horizontal Irradiance

Wind speed
Clouds/wind/weather control the output of solar and wind power plants

Utilities control their conventional generators and market purchases
Clouds/wind/weather control the output of solar and wind power plants

Utilities control their conventional generators and market purchases
A 20 MW ramp is about equivalent to the demand of 10,000 homes.
Different utility operations occur on different time scales

- Minutes: Grid inertia, gas peakers
- Hours: Gas CC, trading
- Days: Coal plants, fuel purchases, trading
- Seasons: Maintenance, construction
- Years: New: batteries, demand response, curtailment
Different forecasting methods work better at different time scales

- Minutes
- Hours
- Days
- Seasons
- Years

- Sensor Networks
- Satellite Imagery
- Numerical Weather Models
- Climate Models
Renewable energy forecast applications

How can forecasts help utilities keep energy costs low and maintain grid reliability?

- Improve energy market trading strategies
- Schedule and invest in more efficient generators (e.g. combined cycle vs. combustion turbine)
- Schedule and invest in transmission
- Reduce costs associated with generator starts
- Defer maintenance associated with excessive generator set point seeking
- Optimize the use of battery storage
Simple benchmark forecast methods

1. Clear sky
2. Persistence
3. Clear sky index persistence
Clear sky forecast

Mean absolute error
The power 5 minutes from now will be the same as it is now

\[ \hat{y}(t_i) = y(t_i - d) \]
Persistence forecast

The power 1 hour from now will be the same it is now

\[ \hat{y}(t_i) = y(t_i - d) \]
Clear sky index persistence forecast

Clear Sky Index = Observations / Clear Sky Expectation
Clear sky index persistence forecast

The clear sky index 1 hour from now will be the same as it now

\[ \hat{y}(t_i) = y(t_i - d) \]
The power 1 hour from now will be the same as it now, but account for solar position

\[ \hat{y}(t_i) = y^{clr}(t_i) k(t_i - d) \]
Day ahead persistence forecast
Day ahead persistence forecast
Day ahead persistence forecast

Normalized Power

01-01 00:00 01-01 12:00 01-02 00:00 01-02 12:00 01-03 00:00 01-03 12:00 01-04 00:00 01-04 12:00

(time)
Day ahead persistence forecast
Day ahead persistence forecast

Normalized Power

0.0 0.2 0.4 0.6 0.8 1.0

01-01 00:00 01-01 12:00 01-02 00:00 01-02 12:00 01-03 00:00 01-03 12:00 01-04 00:00 01-04 12:00

time
Day ahead persistence forecast
Day ahead persistence forecast

The diagram shows a persistence forecast for normalized power over time, with distinct peaks and troughs. The x-axis represents time, while the y-axis represents normalized power. The forecast illustrates the power levels at various time intervals, with notable fluctuations around 01-01 12:00, 01-02 12:00, 01-03 12:00, and 01-04 12:00.
Numerical Weather Prediction at UA

- UA WRF Model highlights
  - 5.4 km outer domain, 1.8 km inner domain
  - Initialized on the 0Z, 6Z, 12Z, 18Z GFS and NAM
  - In summer, 13Z and 15Z RAP initialization

- Local challenges include:
  - Mountains + moisture + heating = monsoon storms
  - Unreliable initialization data from Mexico
  - Extreme planetary boundary layer heights
  - Rapidly changing land/surface characteristics

- 1.8 km resolution, 3 minute outputs of:
  - GHI, DNI, 10 m wind, 80 m wind, temp

WRF configuration details:
- RRTMG
- Morrison 2 mom. or SBUYLIN
- Bougeault-Lacarre or ACM2
- Noah LSM

Weather Research and Forecasting (WRF) community model developed at NCAR, NCEP, ESRL, universities, and more
Raw UA WRF forecasts available at atmo.arizona.edu
2.2 Flux-Form Euler Equations

Using the variables defined above, the flux-form Euler equations can be written:

\[ \partial_t U + (\nabla \cdot V) u - \partial_x (p \phi_y) + \partial_y (p \phi_x) = F_U \]
\[ \partial_t V + (\nabla \cdot V) v - \partial_y (p \phi_x) + \partial_x (p \phi_y) = F_V \]
\[ \partial_t W + (\nabla \cdot V) w - g(\partial_z p - \mu) = F_W \]
\[ \partial_t \phi + (\nabla \cdot V) \phi = F_e \]
\[ \partial_t \mu + (\nabla \cdot V) \mu = 0 \]
\[ \partial_t \phi + \mu^{-1}[(\nabla \cdot \nabla \phi) - gW] = 0 \]

along with the diagnostic relation for the inverse density

\[ \partial_t \phi = -\alpha \mu, \]

and the equation of state

\[ p = p_0(R_d \theta/\rho_d\gamma). \]

In (2.3) – (2.10), the subscripts x, y and \( \eta \) denote differentiation,

\[ \nabla \cdot V a = \partial_x (U a) + \partial_y (V a) + \partial_\eta (\Omega a), \]

and

\[ V \cdot V a = U \partial_x a + V \partial_y a + \Omega \partial_\eta a, \]

where \( a \) represents a generic variable, \( \gamma = c_p/c_v = 1.4 \) is the ratio of the heat air, \( R_d \) is the gas constant for dry air, and \( p_0 \) is a reference pressure (typically right-hand-side RHS terms \( F_U, F_V, F_W, \) and \( F_e \) represent forcing terms a physics, turbulent mixing, spherical projections, and the earth’s rotation.

2.3 Inclusion of Moisture

Water phase changes

In formulating the moist Euler equations, we retain the coupling of dry air mass to the prognostic variables, and we retain the conservation equation for dry air (2.7), as opposed to coupling the variables to the full (moist) air mass and hence introducing source terms in the mass conservation equation (2.7). Additionally, we define the coordinate with respect to the dry-air mass. Based on these principles, the vertical coordinate can be written as

\[ \eta = (p_{\text{d,atm}} - p_{\text{d,th}})/\mu_d \]

where \( \mu_d \) represents the mass of the dry air in the column and \( p_{\text{d,th}} \) and \( p_{\text{d,atm}} \) represent the hydrostatic pressure of the dry atmosphere and the hydrostatic pressure at the top of the dry atmosphere. The coupled variables are defined as

\[ V = \mu_d V, \quad \Omega = \mu_d \Omega, \quad \Theta = \mu_d \Theta. \]

With these definitions, the moist Euler equations can be written as

\[ \partial_t U + (\nabla \cdot V) u + \mu_d \alpha \partial_x p + (\alpha/\alpha_d) \partial_y \partial_\eta p \partial_\eta \phi = F_U \]
\[ \partial_t V + (\nabla \cdot V) v + \mu_d \alpha \partial_y p + (\alpha/\alpha_d) \partial_x \partial_\eta p \partial_\eta \phi = F_V \]
\[ \partial_t W + (\nabla \cdot V) w - g[(\alpha/\alpha_d) \partial_\eta p - \mu_d] = F_W \]
\[ \partial_t \phi + (\nabla \cdot V) \phi = F_e \]
\[ \partial_t \mu_d + (\nabla \cdot V) \mu_d = 0 \]
\[ \partial_t \phi + \mu_d^{-1}[(\nabla \cdot \nabla \phi) - gW] = 0 \]
\[ \partial_t Q_m + (\nabla \cdot V q_m) = F_{Q_m} \]

with the diagnostic equation for dry inverse density

\[ \partial_t \phi = -\alpha_d \mu_d \]

3.1.1 Runge-Kutta Time Integration Scheme

The RK3 scheme, described in Wicker and Skamarock (2002), integrates a set of ordinary differential equations using a predictor-corrector formulation. Defining the prognostic variables in the ARW solver as $\Phi = (U, V, W, \Theta, \phi', \mu', Q_m)$ and the model equations as $\Phi_t = R(\Phi)$, the RK3 integration takes the form of 3 steps to advance a solution $\Phi(t)$ to $\Phi(t + \Delta t)$:

$$
\begin{align*}
\Phi^* &= \Phi^t + \frac{\Delta t}{3} R(\Phi^t) \\
\Phi^{**} &= \Phi^t + \frac{\Delta t}{2} R(\Phi^*) \\
\Phi^{t+\Delta t} &= \Phi^t + \Delta t R(\Phi^{**})
\end{align*}
$$

UA medium res. model
5.4 km grid, SW US
Global Horiz. Irradiance
UA medium res. model
5.4 km grid, SW US
10 m wind speed
UA high res. model
1.8 km grid, AZ and NM
10 m wind speed

Much more wind at lower elevations

Stronger winds along Mogollon rim

Stronger mountain winds

Difference between 5.4 km and 1.8 km domains increases as weather becomes more severe
Solar power forecast from weather model
Wind power forecast from weather model

![Wind power forecast graph]
Weather forecasts are not perfect

Forecast irradiance on Feb 18, 2017

Observed irradiance

Power forecast wrong by 100 MW at 10 AM!

Primary causes of bad forecasts: Initial conditions, microphysics, planetary boundary layer
Limit analysis to large (MAE > 60) errors.
Eliminates clear days.
Helps HRRR, relatively, since it is much worse than UA on clear days.
UA day 3 still outperforming NCEP HRRR
Partnered with local PV installer Technicians for Sustainability to obtain access to real-time (5 min latency) data feeds from residential PV systems.

Prototype: Homebuilt irradiance sensors will cell modems (see A. Lorenzo, AMS 2015).

Network of rooftop solar data and irradiance sensors provides most accurate 30 minute forecasts.
Sensor network forecast

Looks a lot like a persistence forecast!

Combine data from many sensors using statistical methods

Lorenzo et. al., Solar Energy 2015
Sensor network interpolation

Greater Tucson Area

Wind vector

latitude

longitude
Comparing Irradiance Forecast Errors

RMSE (W/m²)

Forecast Horizon (min)

Clearsky
UA-WRF
Measurement Pers.
Clear-Sky Pers.
Network
Satellite Derived Irradiance

Light reflected from the tops of clouds

Light that gets through clouds

[Diagram showing satellite imagery with annotations]
Ground irradiance data to improve satellite irradiance estimates

Satellite irradiance estimates rely on algorithms that convert the observation (light reflected by cloud tops) into transmitted irradiance.

Use ground PV and irradiance data to improve estimates

Unique method developed at UA

Published in Solar Energy (Lorenzo 2017)
More from Travis Harty this afternoon!

Comparing Irradiance Forecast Errors

RMSE (W/m²)

Forecast Horizon (min)

Clearsky
UA-WRF
Measurement Pers.
Clear-Sky Pers.
Network
Base Satellite Img.
Satellite Img. after
Optimal Interpolation
Satellite
Taylor diagram: RMSE is not enough

\[ \text{RMSE}^2 = \sigma_f^2 + \sigma_r^2 - 2\sigma_f \sigma_r R + \text{MBE}^2 \]

\[ \cos^{-1} R \]

\[ \sigma_f \]

\[ E' \]

\[ \sigma_r \]

Figure 1. Geometric relationship between the correlation coefficient \( R \), the centered pattern RMS error \( E' \), and the standard deviations \( \sigma_f \) and \( \sigma_r \) of the test and reference fields, respectively.
Taylor diagram: RMSE is not enough

<table>
<thead>
<tr>
<th></th>
<th>A</th>
<th>B</th>
<th>C</th>
</tr>
</thead>
<tbody>
<tr>
<td>MBE</td>
<td>0.00</td>
<td>0.02</td>
<td>0.01</td>
</tr>
<tr>
<td>MAE</td>
<td>0.10</td>
<td>0.09</td>
<td>0.12</td>
</tr>
<tr>
<td>RMSE</td>
<td>0.16</td>
<td>0.13</td>
<td>0.16</td>
</tr>
<tr>
<td>Correlation</td>
<td>0.49</td>
<td>0.53</td>
<td>–</td>
</tr>
<tr>
<td>Std. Dev.</td>
<td>0.15</td>
<td>0.07</td>
<td>0.00</td>
</tr>
</tbody>
</table>
Taylor diagram: RMSE is not enough
Taylor diagram: RMSE is not enough

\[ \text{RMSE}^2 = \sigma_f^2 + \sigma_r^2 - 2\sigma_f \sigma_r \text{R} + \text{MBE}^2 \]

The best forecast has
1. The lowest error AND
2. The same variance as the observed signal
PVLib Python

- Tool for modeling solar power systems
- Foundation of the UA power forecasts
- Open source
- Descendant of Sandia’s PVLIB MATLAB
- Primarily coordinated by Will, with contributions from across the world.
- Solar power forecast module funded by EPRI and Southern Company
- [github.com/pvlib](https://github.com/pvlib)
PVLIB Python statistics

Known users include:

1. Sandia National Lab
2. NREL
3. Sun Power
4. First Solar
5. NCAR
6. Fraunhofer ISE
7. Sunshine Analytics
8. Solar City
9. Itron
10. PV Performance Laboratories
11. Reiner Lemoine Institute
12. Strata Solar Services
13. Stuart Bowden (ASU)

As of October 18, 2017...

Issues: 42 Open 162 Closed
Pull requests: 5 Open 178 Closed
934 commits 4 branches 18 releases 28 contributors

Issues:

1. Pull requests:
# PVLib Python forecasts

**The problem:** weather forecast data is a mess!

<table>
<thead>
<tr>
<th>Model</th>
<th>GHI</th>
<th>DNI</th>
<th>Cloud cover</th>
</tr>
</thead>
<tbody>
<tr>
<td>GFS, 0.5 deg</td>
<td>3/6 hr mixed interval average</td>
<td>None</td>
<td>3/6 hr mixed interval average</td>
</tr>
<tr>
<td>NAM, 12 km</td>
<td>1 hr for 36 hrs 3 hr for 84 hrs</td>
<td>None</td>
<td>1 hr for 36 hrs 3 hr for 84 hrs</td>
</tr>
<tr>
<td>RAP, 13 km</td>
<td>None</td>
<td>None</td>
<td>1 hr instant</td>
</tr>
<tr>
<td>UA-WRF, 1.8 km</td>
<td>3 min. instant 3 min. instant</td>
<td>3 min. instant</td>
<td>None</td>
</tr>
</tbody>
</table>

**A solution:** standardized data processing in PVLib Python
PVLib Python forecasts

Get relevant weather forecast data in 5 lines of code

from pvlib.forecast import GFS, NAM, RAP, HRRR

lat, lon = 32.2, -110.9

start, end = pd.Timestamp('20171018'), pd.Timestamp('20171025')

fx_model = GFS()

fx_data = fx_model.get_processed_data(lat, lon, start, end)
lat, lon = 32.2, -110.9
start, end = pd.Timestamp('20171018'), pd.Timestamp('20171025')

from pvlib.forecast import GFS, NAM, RAP, HRRR

fx_model = GFS()
fx_data = fx_model.get_processed_data(lat, lon, start, end)
PVLib Python forecasts

Convert your weather forecast into a power forecast in 5 lines of code

```python
module_parameters = {'pdc0': 10.0, 'gamma_pdc': -0.0035}

system = SingleAxisTracker(module_parameters=module_parameters)

location = Location(lat, lon)

mc = ModelChain(system, location, **model_parameters)

mc.run_model(times=fx_data.index, weather=fx_data)
```
Single Axis Tracker PV Power Forecast from GFS Model
Replace GFS() with NAM()
Rerun code
You too can be a forecaster!

1. Define your forecast problem
2. Determine what’s “good enough”
3. Select an appropriate forecast method and data set

If working in solar...

4. Use PVLib Python or PVLib Matlab for PV modeling
5. Help me make PVLIB better for everyone
Thanks to our funding agencies

Major support from

DOE EERE Postdoctoral Fellowship

RESEARCH, DISCOVERY & INNOVATION
Institute for Energy Solutions

Additional support from

The SVERI utilities

Arizona Department of Environmental Quality