mePV

CE 186 Fall 2016

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Energy Crisis - The Necessary Shift to Renewables

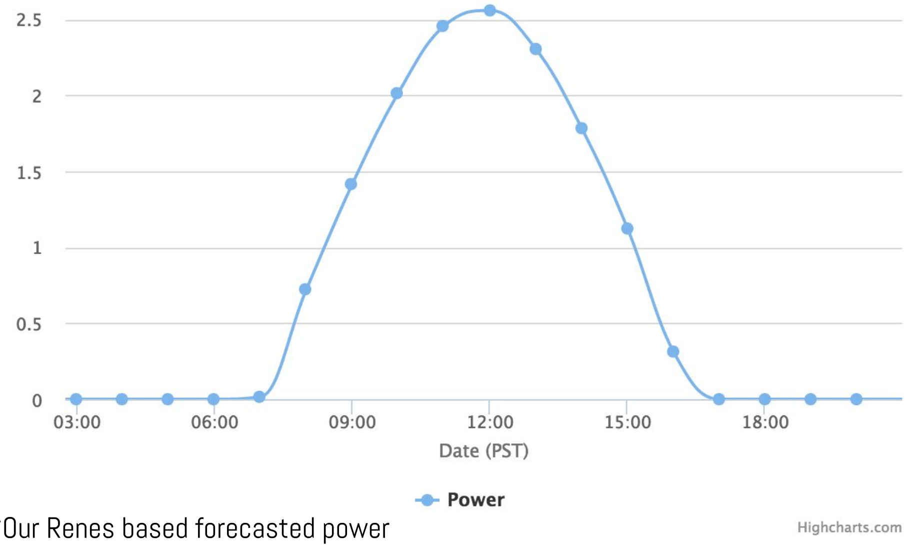
- 48% increase in energy consumption from 2012 to 2048 (IEOE)
- 1.2 billion people without access to electricity in 2016 (WEO)
- Photovoltaics and efficient devices are more effective and less expensive than ever
- Opportunity for solar industry and technological leapfrogging

Solar Forecasting

- What is it?
- What specifically does it apply to?
  - Off the grid
  - In your home
  - Microgrids
  - In the grid itself

Renes
The TUC Renewable Energy Estimator

PVWatts® Calculator



*Our Renes based forecasted power

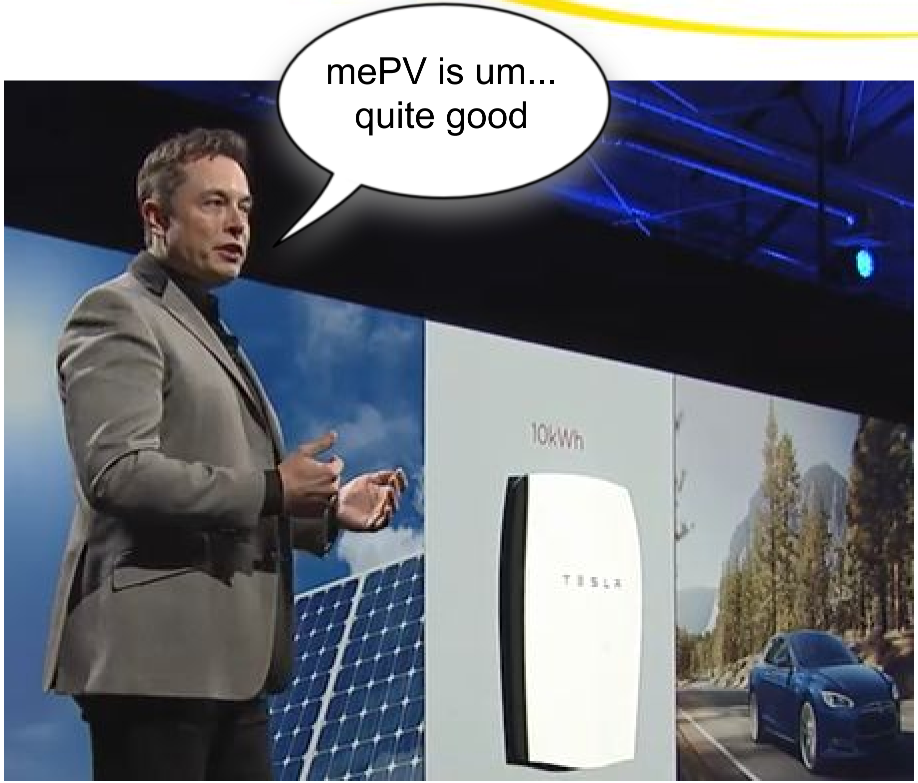
Off the grid

This is Ted...

- Ted lives in a tiny house off the grid
- Solar forecasting allows Ted to proactively manage his use of energy given how much he can expect to produce the next day

In your home

- Minimize use of grid electricity
- Minimize cost (tier pricing)
- Optimize EV charging
- Combine with WattTime

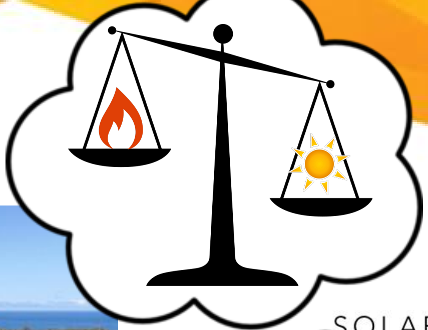


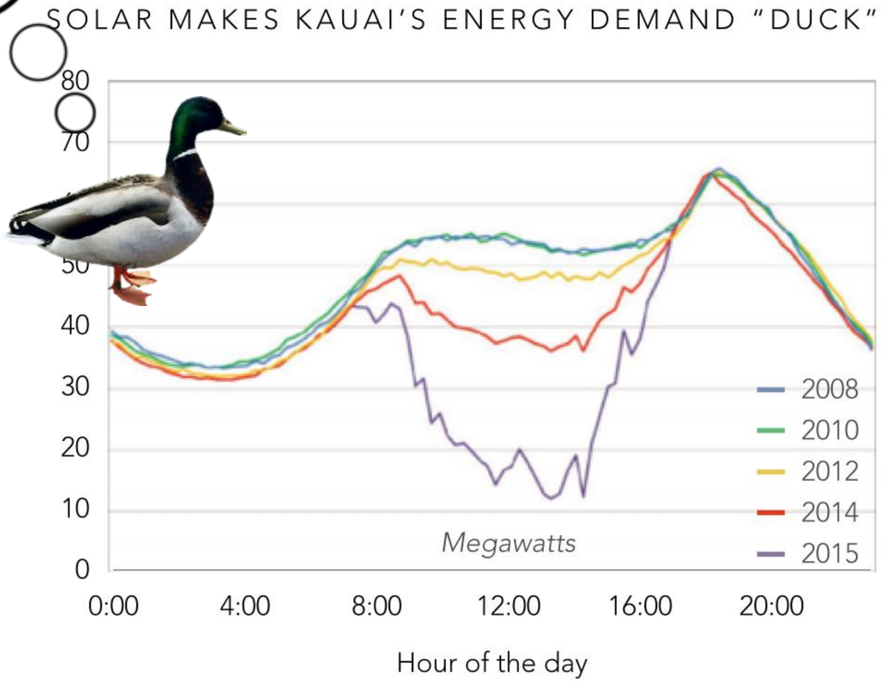
Microgrids

- Manage communal loads and storage proactively based on forecasted solar generation

- Forecasting can increase microgrid resilience to weather events

In the grid




SOLAR MAKES KAUAI'S ENERGY DEMAND "DUCK"
80
70
40
30
20
10
0
Megawatts
2008
2010
2012
2014
2015
0:00
4:00
8:00
12:00
16:00
20:00
Hour of the day

Introducing: mePV

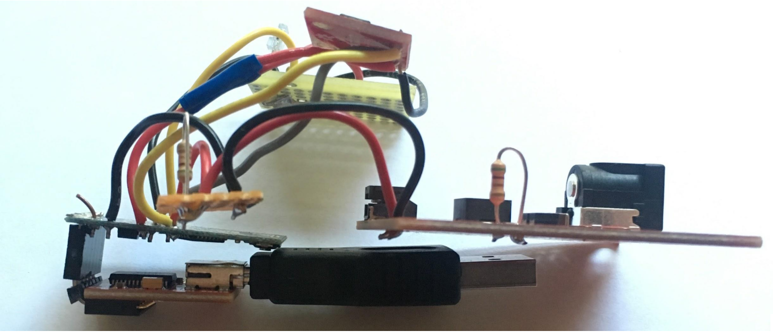
Why is our product *different*?

mePV is a *consumer-scale machine-learning* system for PV power forecasting

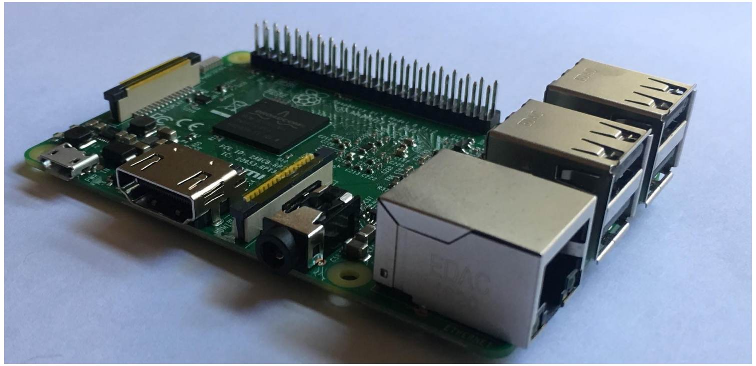
Running automatically, it adapts to new data without human interference

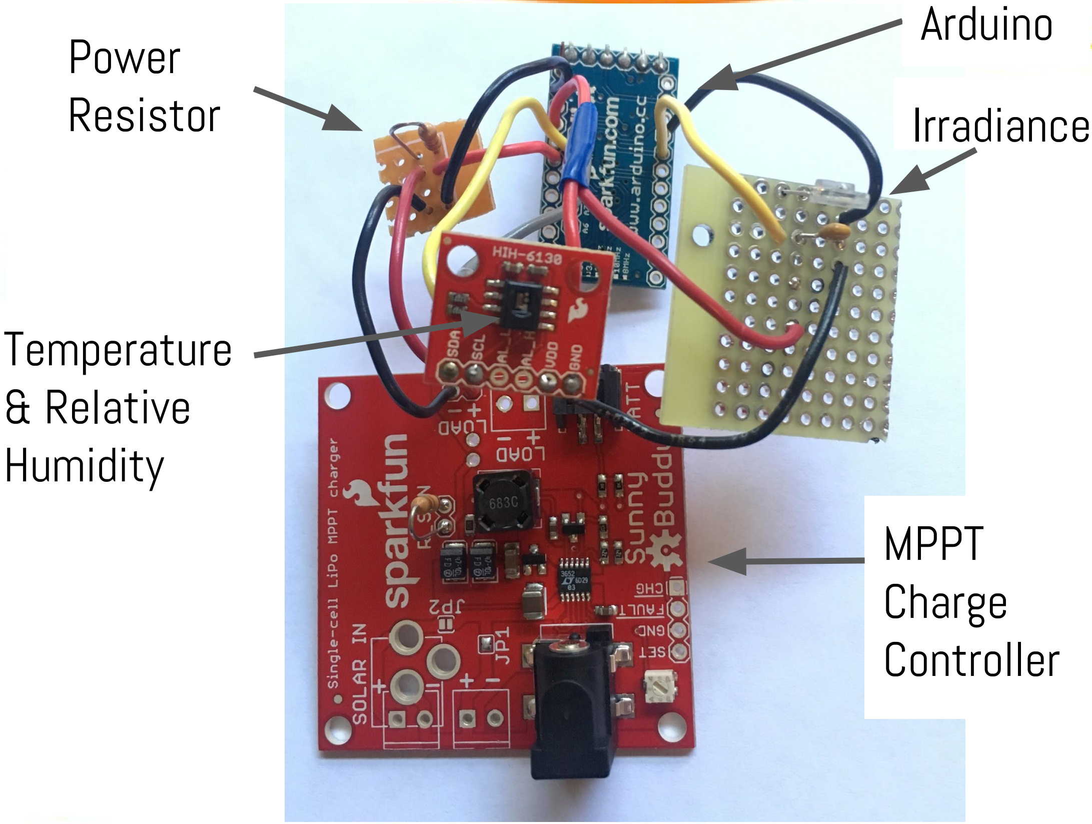
Hardware

Arduino Pro Mini and sensor network



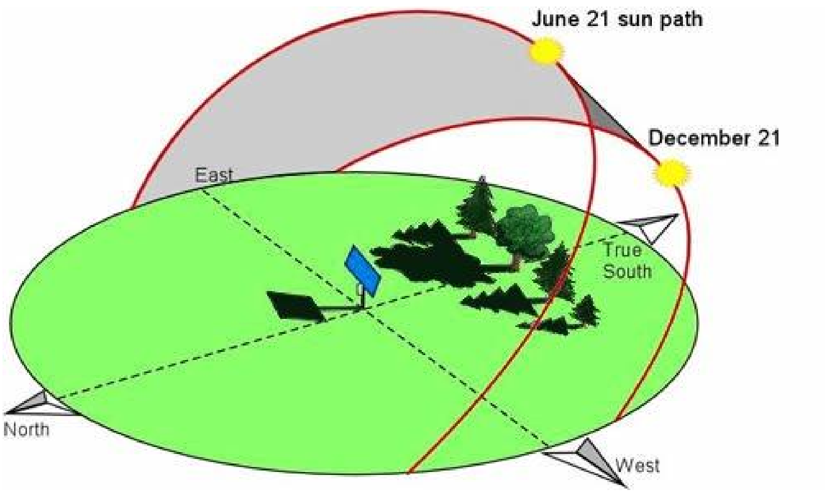
Raspberry Pi 3 Model B



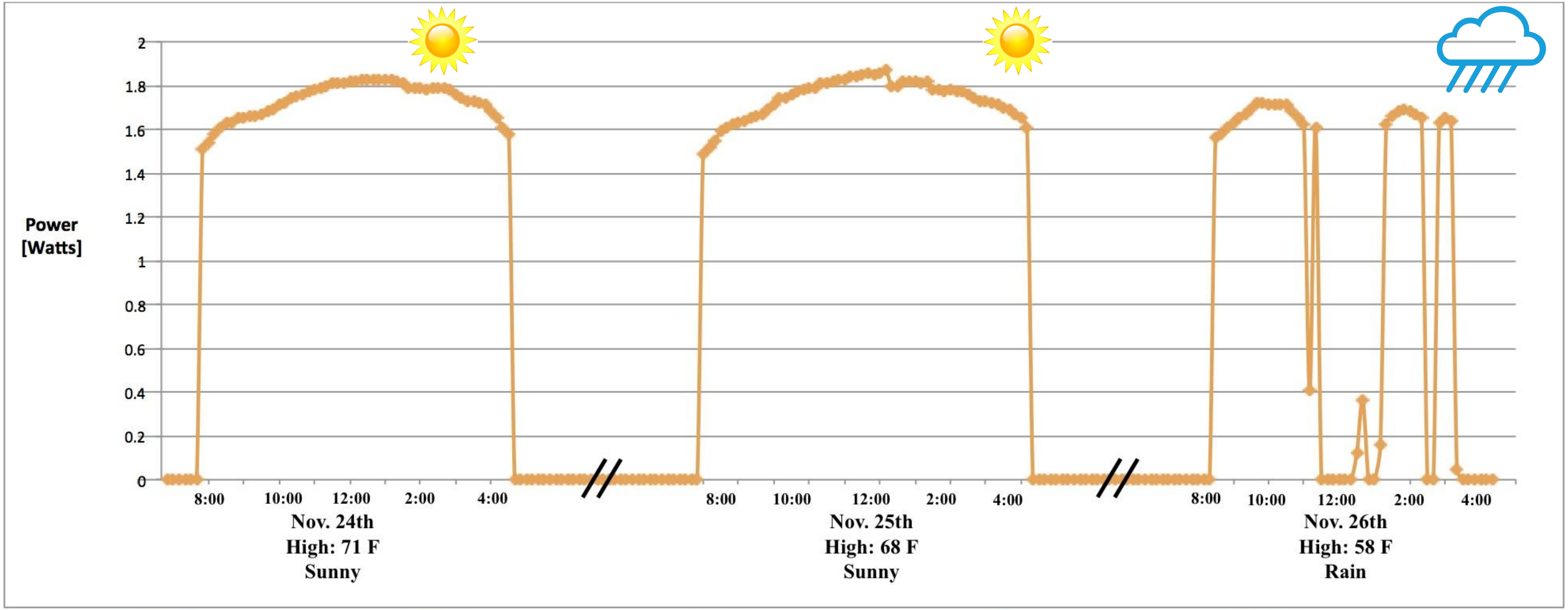


Data Collection

- Array location characteristics
- Seasonal considerations
- Weather events

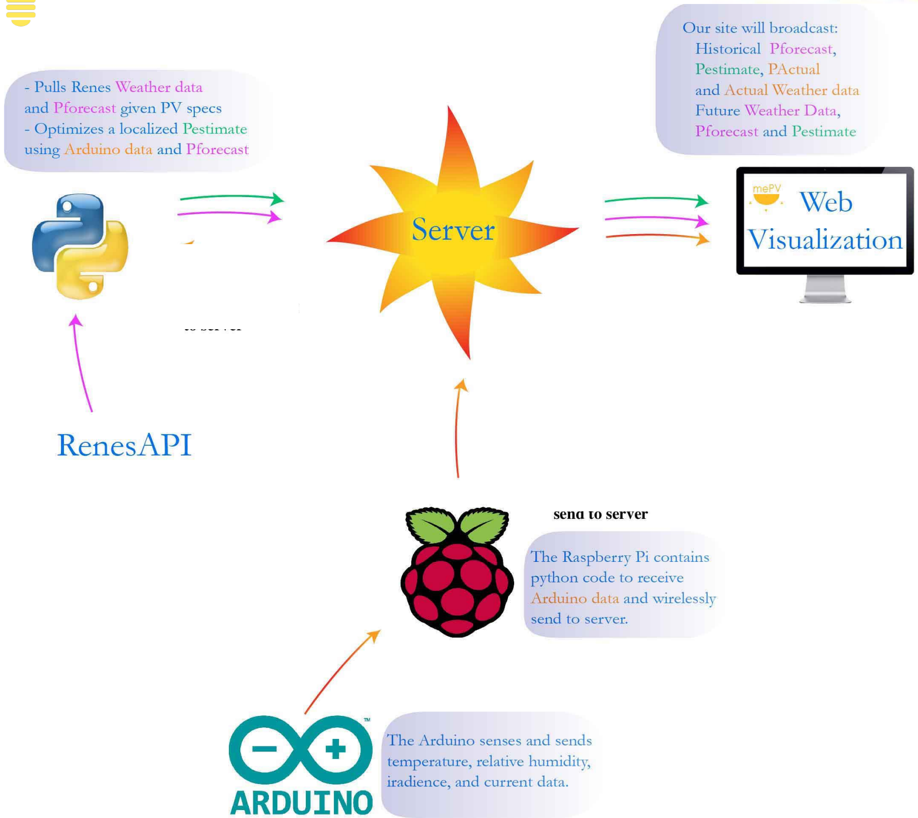


Three days of real power data representative of unique PV conditions

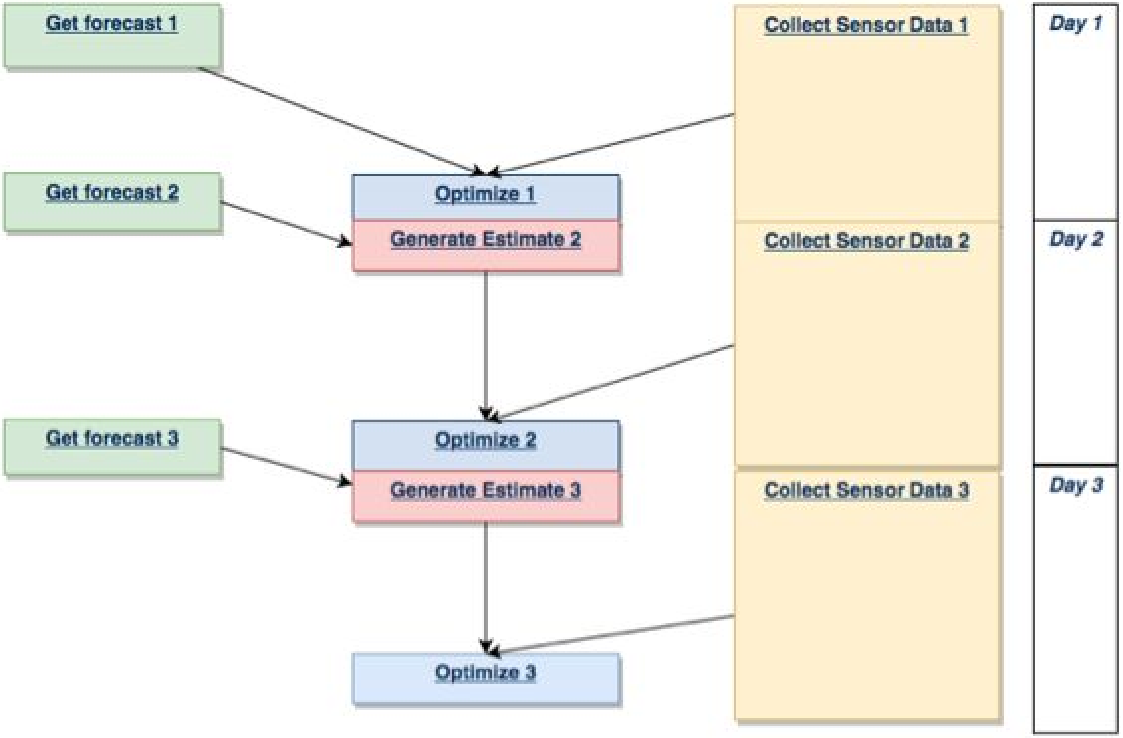


Connectivity

P_measured (Real)
P_forecast (RENES)
P_estimate (mePV)



Optimization



Creating the mePV Forecast

For any day j the optimization to solve for $\theta(j)$ is:

$$\min \| (\theta_1 P_{est}(j) + \theta_2 T_{true}(j) + \theta_3 H_{true}(j) + \theta_4 I_{true}(j) + \theta_5) - P_{true}(j) \|^2$$

$$P_{est} \epsilon \mathbb{R}^{24} \quad T \epsilon \mathbb{R}^{24} \quad H \epsilon \mathbb{R}^{24} \quad I \epsilon \mathbb{R}^{24} \quad \theta \epsilon \mathbb{R}^{5} \quad P_{true} \epsilon \mathbb{R}^{24}$$

Approach 1
(Daily Data)

Approach 2
(Hourly Data)

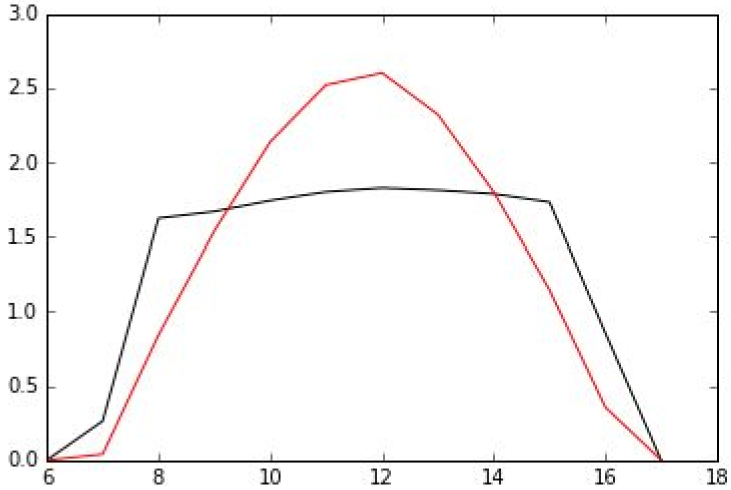
Stacked Retrospective Rolling-Horizon Optimization

Optimization 01

At 00:01AM, use Thursday's data to calculate mePV Forecast for Friday

Power output: Watts

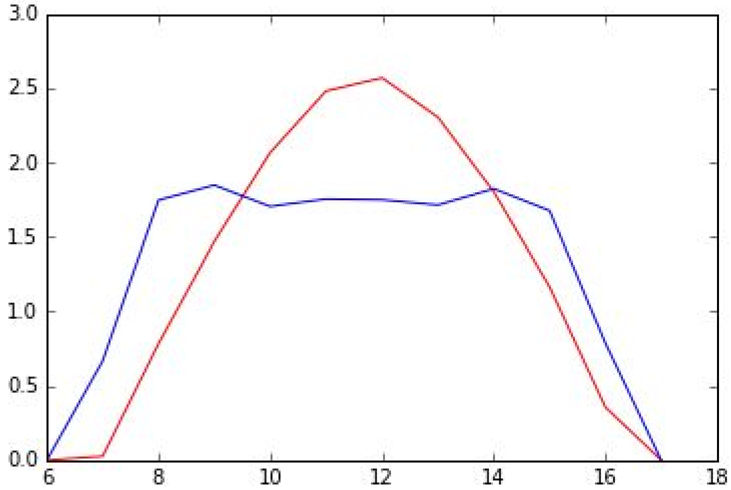
Thursday



Sunlight hours [7:00-16:00]

Renes Forecast: Red
Actual Power: Black

Friday



Sunlight hours [7:00-16:00]

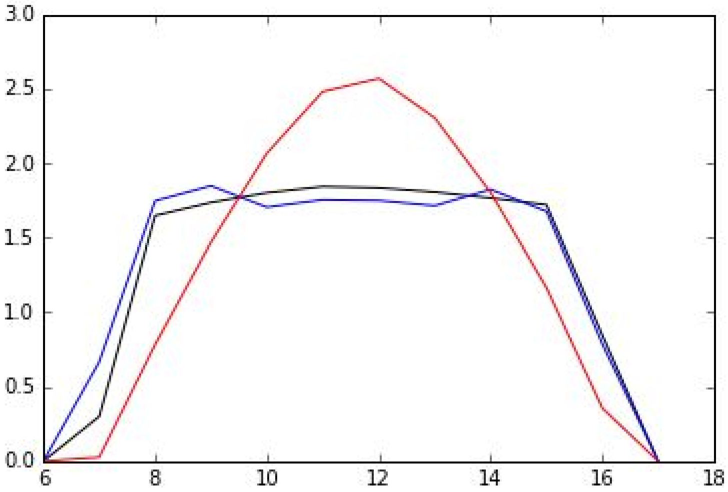
Renes Forecast: Red
mePV Forecast: Blue

Optimization 02

At 00:01AM, use Friday's data to calculate mePV Forecast for Saturday

Power output: Watts

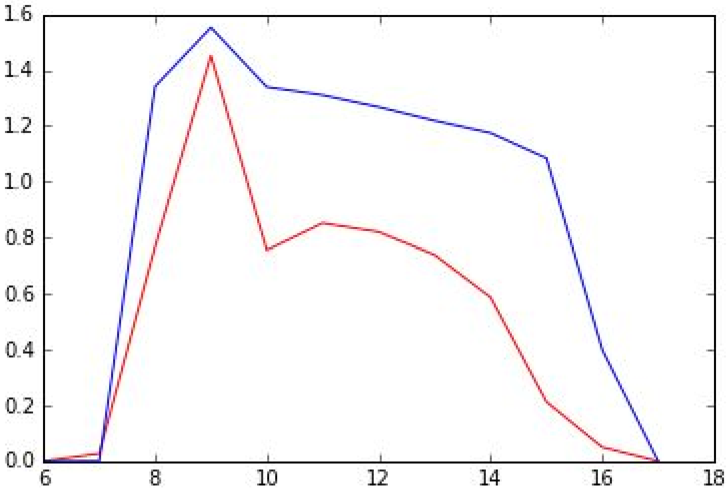
Friday



Sunlight hours [6:00-18:00]

Renes Forecast: Red
mePV Forecast: Blue
Actual Power: Black

Saturday



Sunlight hours [6:00-18:00]

Renes Forecast: Red
mePV Forecast: Blue

Web Visualization

https://mepv-bornap.c9users.io/

Why does it matter?

- Traditional solar forecasting for a single-system demonstrates error of 30 - 40% rRMSE. (Lorenz et. al.)
- Forecasts can help utility providers and regulators add stability to the grid and avoid the waste of energy.

mePV as a Product

- Affordable, wireless, and compact
- Easily deployable for Microgrid and Off-grid usage with customizable load profiling
- Minimize electricity costs due informed energy sourcing in a tiered electricity economy

Next steps

- Continue collecting data and perfecting our optimization
- Improve stacked parallel optimization parameters
- Add additional optimization models into stacked ensemble
- Add load profiling options for users
- Become Elon Musk

Creating the mePV Forecast

mePV_loop runs three functions: both optimizations and RENES API request

```
#The mePV loop runs in the background of the computer, set to run each day at
#12:01 AM. It imports two optimization approaches, requests the weather and power
#forecast from Renes API, and calculates the Pestimate for the next day

import schedule
import time

def job():

    import optimize_24
    import optimize_hourly
    import renes_requestandstore

schedule.every().day.at("00:01").do(job)
while True:
    schedule.run_pending()
    time.sleep(True)
```

```
#OPTIMIZATION
ones = 24*[1.0]

if len(Pest) == 0:
    Pest = Pfore_daylight
#otherwise, Pest is the values pulled from

X = zip(Pest, Tfore_daylight, Hfore_daylight, Ifore_daylight,ones)


olsmod = sm.OLS(Ptrue_daylight, X)
olsres = olsmod.fit()
print(olsres.summary())


ypred = olsres.predict(X)
print(ypred)

plt.plot(hour_graph, ypred, color='blue')

#Save Coefficients to local dictionary
coef_dict_daily['Coef_save_' + str(now.month) +'_' + str(now.day)]=[]
coef_dict_daily['Coef_save_' + str(now.month) +'_' + str(now.day)].append(ypred)
#Save coefficients to disk
numpy.save('Coef_save_' + str(now.month) +'_' + str(now.day),reg.coef_)
```

```
#Calculate PEST Using the Stacked Combination of Both Sets of Regression Coefs
Pest=[]

for u in range(0,10):

    Stacked_Estimate=Pfore_tmrw_day[u]*stack[u][0] + Tfore_tmrw_day[u]*stack[u][1] +
    if Stacked_Estimate < 0:
        Stacked_Estimate=0
    Pest.append(Stacked_Estimate)


plt.figure(50)
plt.plot(Pfore_tmrw_day, color='red')
plt.plot(Pest, color='blue')
```

Creating the mePV Forecast

Combined Retrospective Rolling Horizon Optimization
=

Linear Regression Approach 1 (Daily Data)

+

Linear Regression Approach 2 (Hourly Data)

Approach 1:

Optimizing data from **entire day (24 points in each dataset)** with a general solution for the day that is not specific to any hour i =24:

For any day j the optimization to solve for $\theta(j)$ is:

$$\min \| (\theta_1 P_{est}(j) + \theta_2 T_{true}(j) + \theta_3 H_{true}(j) + \theta_4 I_{true}(j) + \theta_5) - P_{true}(j) \|^2$$

$$P_{est} \epsilon \mathbb{R}^{24} \quad T \epsilon \mathbb{R}^{24} \quad H \epsilon \mathbb{R}^{24} \quad I \epsilon \mathbb{R}^{24} \quad \theta \epsilon \mathbb{R}^{5} \quad P_{true} \epsilon \mathbb{R}^{24}$$

We can define an X matrix that is the concatenation of our input datasets, $X \epsilon \mathbb{R}^{5x24}$

$$\theta(j) = \begin{bmatrix} \theta_1 \\ \theta_2 \\ \theta_3 \\ \theta_4 \\ \theta_5 \end{bmatrix} \quad X(j) = \begin{bmatrix} P_{est,1} & T_{true,1} & H_{true,1} & I_{true,1} & 1 \\ P_{est,2} & T_{true,2} & H_{true,2} & I_{true,2} & 1 \\ P_{est,3} & T_{true,3} & H_{true,3} & I_{true,3} & 1 \\ P_{est,4} & T_{true,4} & H_{true,4} & I_{true,4} & 1 \\ P_{est,5} & T_{true,5} & H_{true,5} & I_{true,5} & 1 \\ \dots & \dots & \dots & \dots & \dots \\ P_{est,24} & T_{true,24} & H_{true,24} & I_{true,24} & 1 \end{bmatrix} \quad Y(j) = P_{true}(j) = \begin{bmatrix} P_{true,1} \\ P_{true,2} \\ P_{true,3} \\ P_{true,4} \\ P_{true,5} \\ \dots \\ P_{true,24} \end{bmatrix}$$

Creating the mePV Forecast

Combined Retrospective Rolling Horizon Optimization
=

Linear Regression Approach 1 (Daily Data)

+

Linear Regression Approach 2 (Hourly Data)

Approach 2:

Optimizing data from **multiple days for a specific hour**, with a solution specific to some hour i that does not apply to any entire day

The optimization to solve for $\theta(i)$ at each hour
Where j = total days of recorded *forecasted* and *true* data

$$\min \| (\theta_1 P_{est}(i) + \theta_2 T_{true}(i) + \theta_3 H_{true}(i) + \theta_4 I_{true}(i) + \theta_5) - P_{true}(i)) \|^2$$

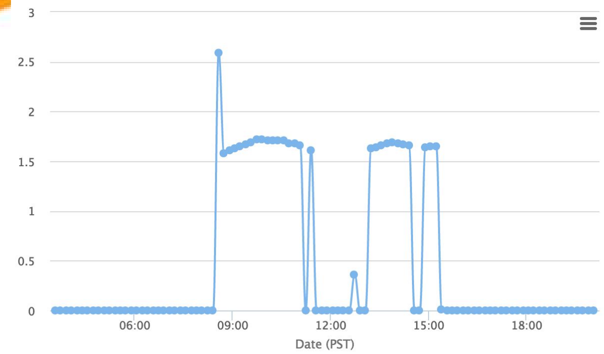
$$P_{est} \epsilon \mathbb{R}^j \quad T \epsilon \mathbb{R}^j \quad H \epsilon \mathbb{R}^j \quad I \epsilon \mathbb{R}^j \quad \theta \epsilon \mathbb{R}^5 \quad P_{true} \epsilon \mathbb{R}^j$$

We will conduct this optimization for each of 24 times

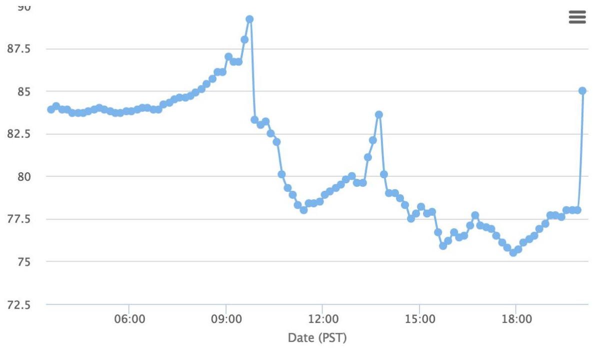
We can define an X matrix that is the concatenation of our input datasets, $X \epsilon \mathbb{R}^{5xj}$

$$\theta(i) = \begin{bmatrix} \theta_1 \\ \theta_2 \\ \theta_3 \\ \theta_4 \\ \theta_5 \end{bmatrix} \quad X(i) = \begin{bmatrix} P_{est,1} & T_{true,1} & H_{true,1} & I_{true,1} & 1 \\ P_{est,2} & T_{true,2} & H_{true,2} & I_{true,2} & 1 \\ P_{est,3} & T_{true,3} & H_{true,3} & I_{true,3} & 1 \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ P_{est,j} & T_{true,j} & H_{true,j} & I_{true,j} & 1 \end{bmatrix} \quad Y(i) = P_{true}(i) = \begin{bmatrix} P_{true,1} \\ P_{true,2} \\ P_{true,3} \\ \cdots \\ P_{true,j} \end{bmatrix}$$

Power



RH



Temp