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# Forecasting Final Presentation

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SCEL

# Overview

1. Motivation
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4. Methods
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# Motivation

## Why is it to important forecast solar irradiance?

- It is difficult to integrate renewable sources into electrical grid
- Electrical grids need to generate power equal to the power needed
- Introducing solar energy adds potential instability
  - E.g. PV panels under producing power leads to the grid under providing power



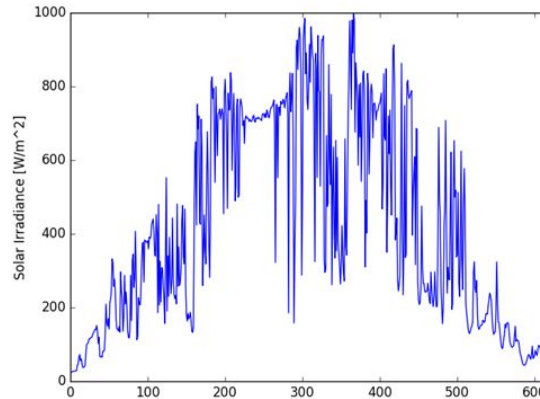
# Objective

To develop an algorithm that is able to forecast future solar irradiance

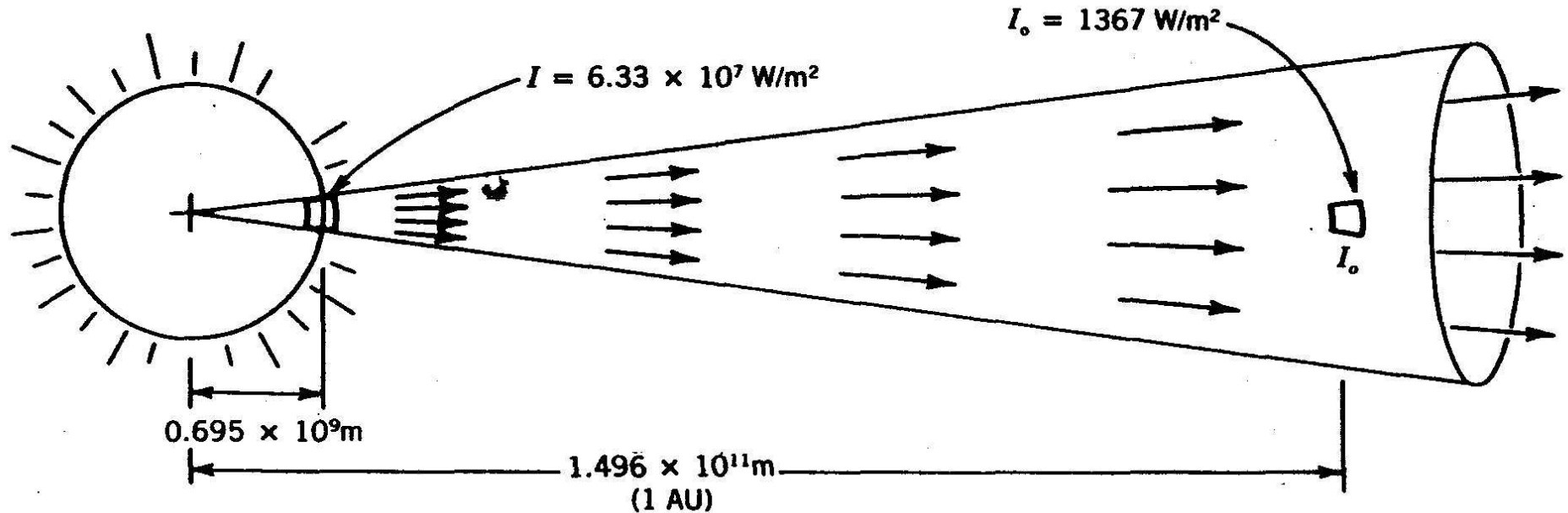
- Online algorithm
  - ◆ Algorithms that takes data one by one
  - ◆ Useful for dealing with large datasets
- Find a method to help account for time of day and seasonal effects
  - ◆ Normalization using the zenith angle

# Predicting Solar Irradiance Using Data Properties

- ▷ In order to make predictions on the data, we need to understand the nature of our data.



# Dispersion of Sunlight throughout Space

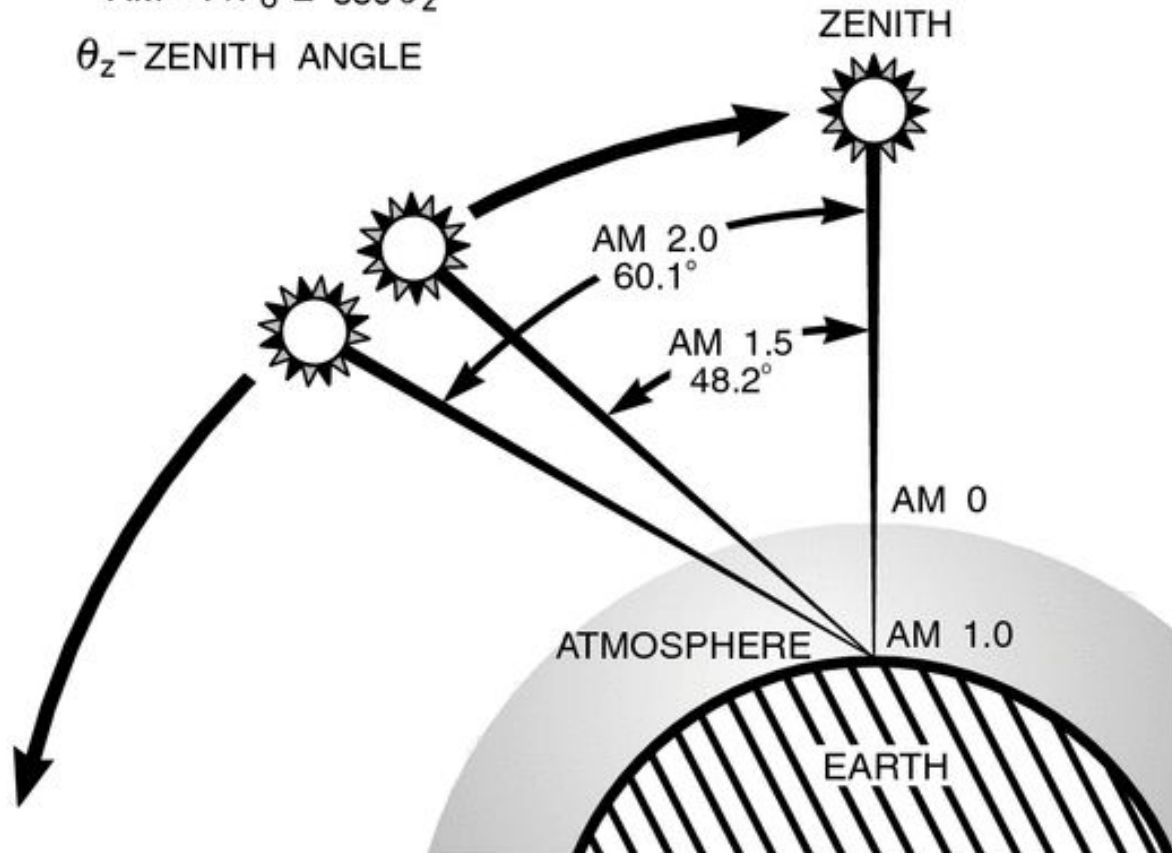


# Effect of Time of Day

$$AM \approx P/P_0 = \sec \theta_z$$

$\theta_z$  - ZENITH ANGLE

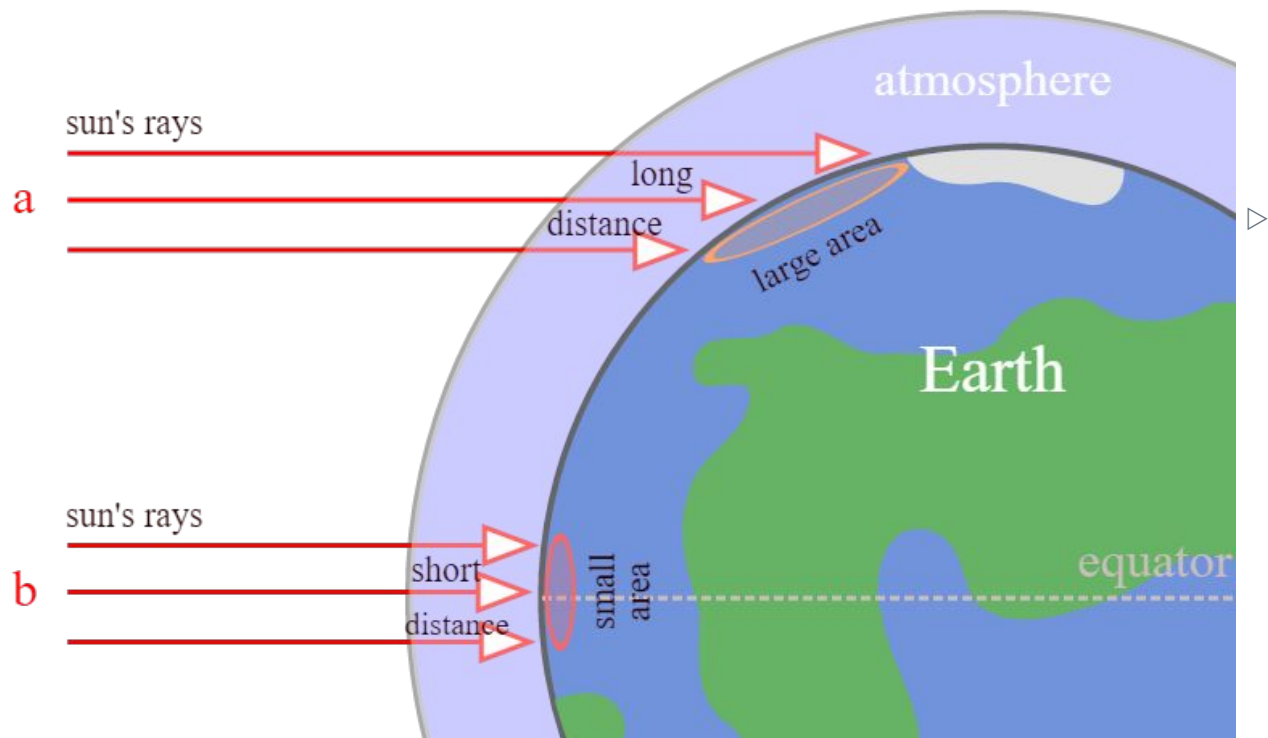
- ▷ As the earth spins throughout the day, the angle of incidence of the solar rays changes
- ▷ The rays travel through Air Mass which causes scattering and dispersion



# Effect of Geographical Location

solar radiation measured in

$$\frac{\text{Watts}}{\text{meters}^2}$$

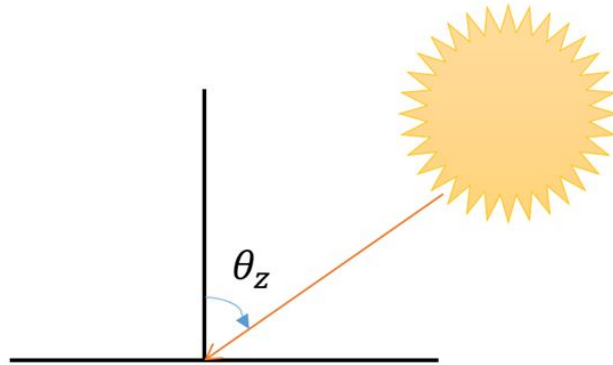


▷ The latitudinal location also affects the solar radiation as this affects both the distance the rays travel through the atmosphere and the area that the ray is distributed on.

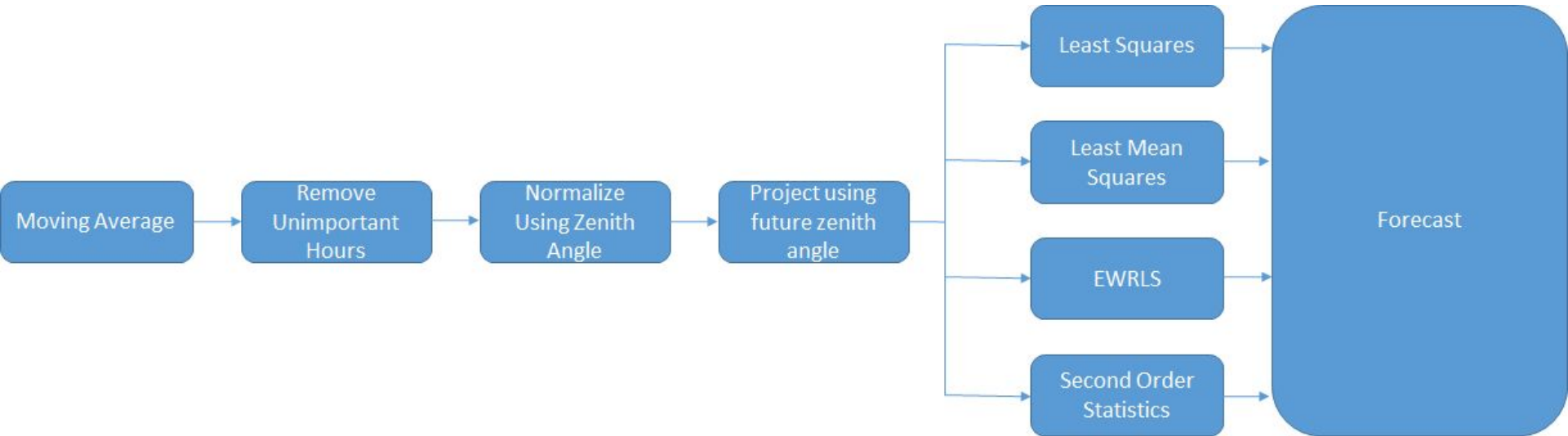


# Features Used

- ▷ Tap Filters
  - Using previous solar irradiance values as inputs
- ▷ Zenith angle

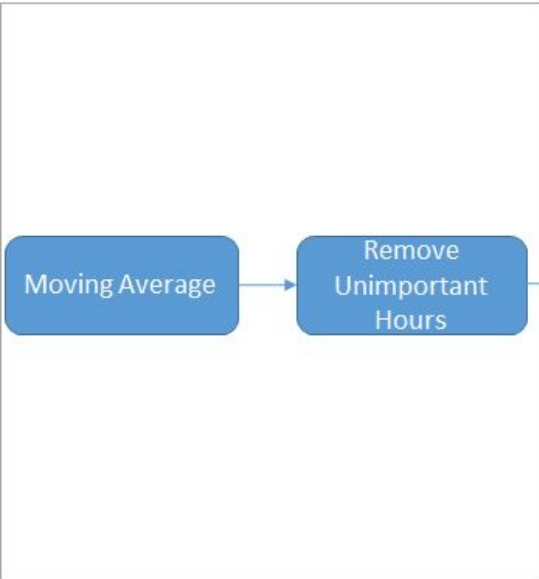


# Block Diagram

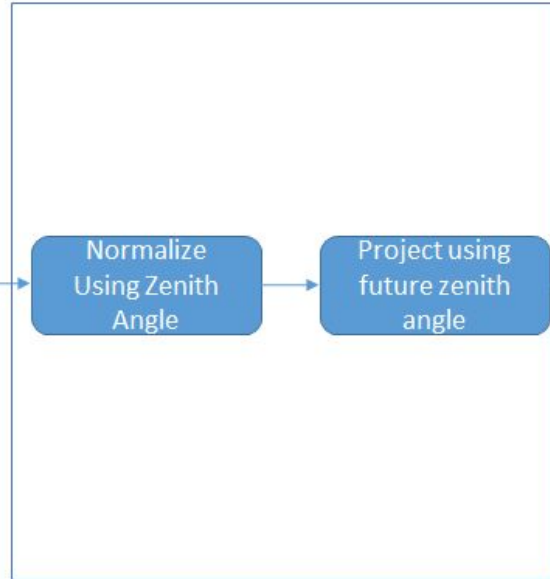


# Block Diagram

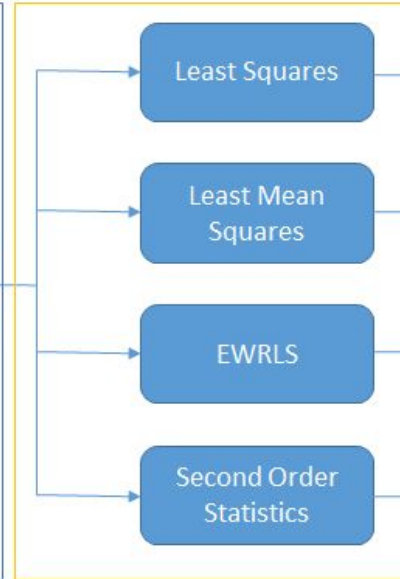
## Preprocess



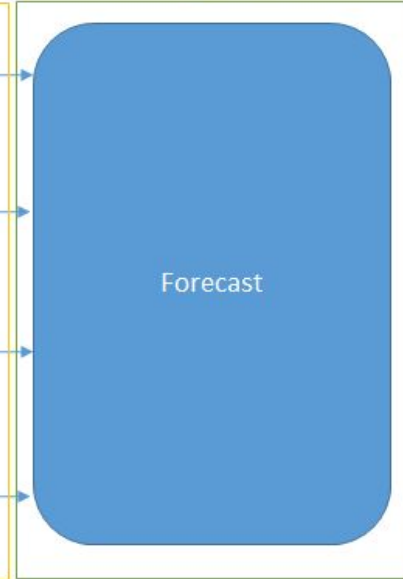
## Normalization



## Train Models

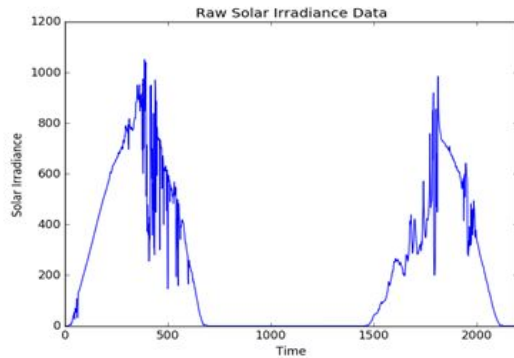


## Forecast

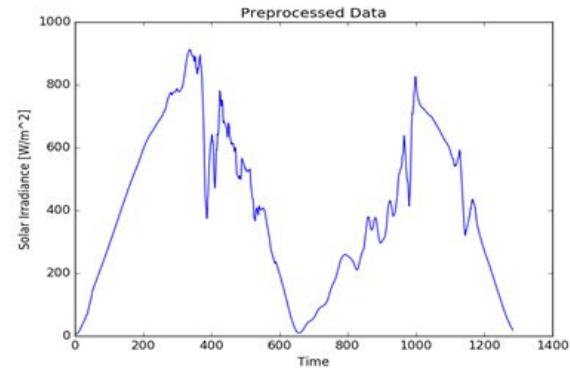


# Preprocessing

- ▷ Conduct moving average on the data to smooth the data
- ▷ Remove hours outside of our interest (night time)



Preprocessing

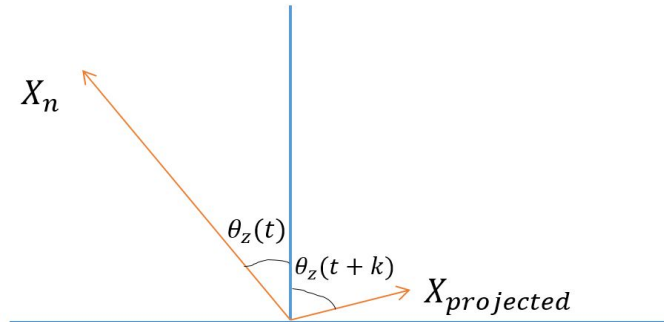


# Normalization

- ▷ Normalize using the zenith angle
  - Removes time of day and seasonal effects
  - Projecting solar irradiance in the direction of a future zenith angle

$$X_n(t) = \frac{R(t)}{\cos\theta_z(t)}$$

$$X_{projected}(t) = X_n(t) * \cos\theta_z(t + k)$$



# Train Model

## Machine Learning Algorithms

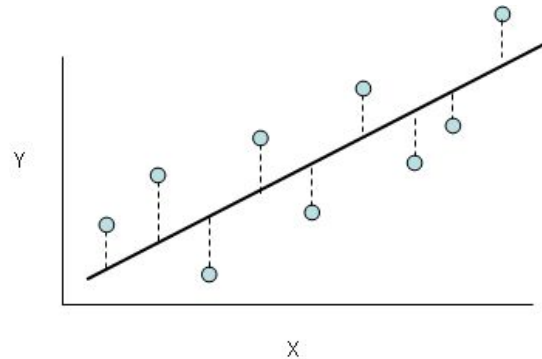
- ▷ Least Squares
- ▷ Least Mean Squares (LMS)
- ▷ Exponential Weighted Recursive Least Squares (EWRLS)
- ▷ Second Order Statistics

## Example of a mathematical model

$$Y = ax^2 + bx + c$$

# Least Squares

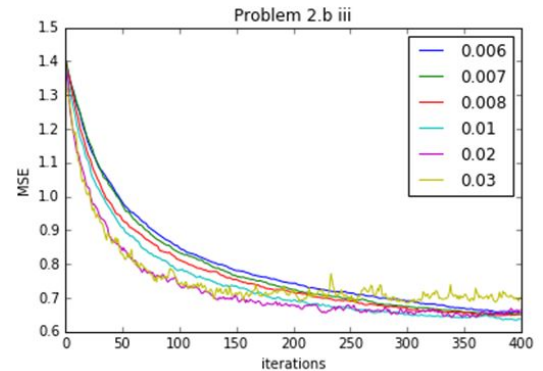
- ▷ Fundamental machine learning algorithm
- ▷ Offline Algorithm
- ▷ Determines weights by minimizing squared error
  - Error is the difference between predicted output and expected output



# Least Mean Squares

- ▷ Estimate optimal weights
- ▷ Online Algorithm
- ▷ Adjusts weights based on error
- ▷ Low complexity and computation time

```
for i in range(0,d.size):  
    x_lms = np.transpose(np.matrix(X[:,i]))  
    d_lms = d[i,0]  
    e = d_lms-W*x_lms.T  
    W = W + step*e.item(0)*x_lms
```





# EWRLS & Second Order Statistics

## EWRLS

- ▷ Online version of least squares
- ▷ Forgetting factor  $\lambda$ 
  - Previous inputs have less impact

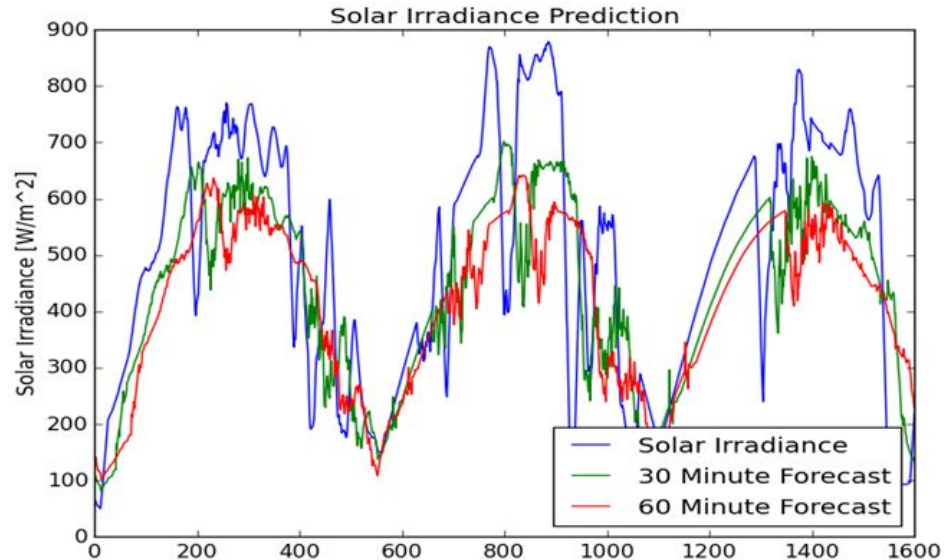
## Second Order Statistics

- ▷ Uses covariances for current solar irradiance and previous solar irradiance to forecast future irradiance

```
lam_i = lam**i-1
for i in range(2,d.size):
    x_n1 = x[0:n,i]
    alpha = (d[i]-np.transpose(w)*x_n1).item(0)
    g = p*x_n1* np.linalg.inv(lam_i + np.transpose(x_n1) * p * x_n1)
    p = lam_i*p - g * np.transpose(x_n1)*lam_i * p
    w = w + alpha * g
```

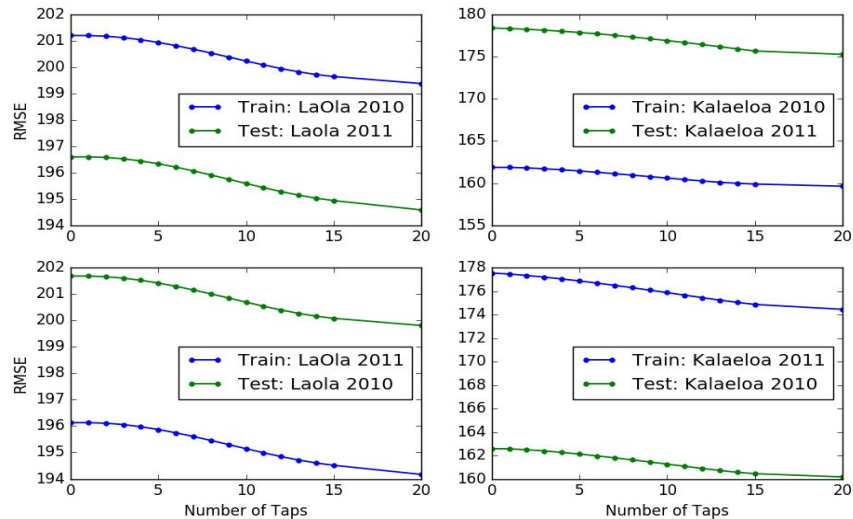
# Forecast

- ▷ Input data into the model and see the results



# Results: Tap Filters

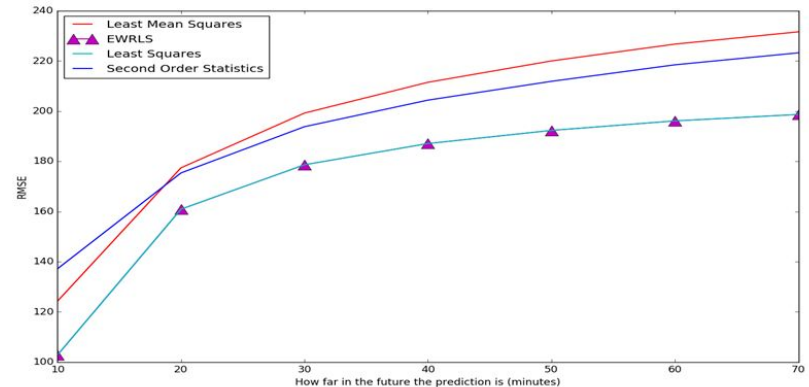
- ▷ Adding tap filters gave little improvements
- ▷ Used two to three taps for algorithms



# Results: Algorithm Comparisons

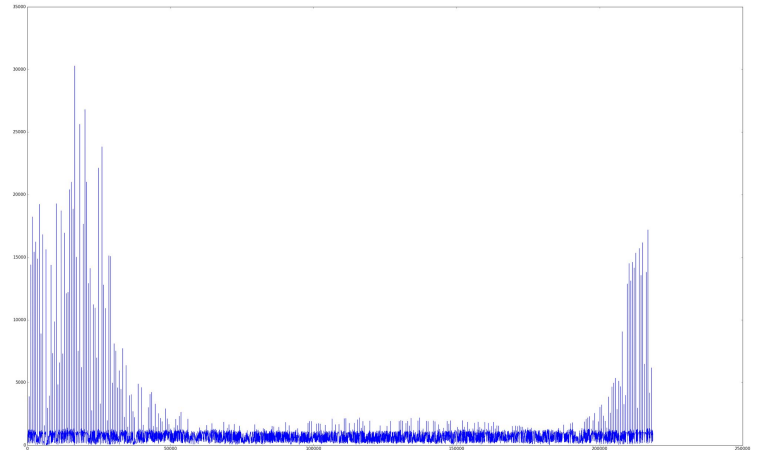
- Best Performance
  - EWRLS and Least Squares
- Computation Time
  - Fastest : LMS
  - Slowest: EWRLS

Algorithm	Run Time (s)
LMS	2.1874
EWRLS	19.7354
Second Order Stats	4.8654



# Problems

- ▷ Working with large datasets
  - Learning techniques to working with large datasets
    - Debugging
- ▷ Zenith angles near 90 degrees
  - Threshold
  - Reduce range of hours



# Remaining Problems

- ▷ Machine learning takes time to learn
  - With older members graduating, it is important for newer members to understand machine learning
- ▷ Solutions
  - Strong Documentation
  - Forecasting researches and develops different methods

# Final Status

1. Developed an online forecasting algorithm
2. Normalization using the zenith angle gives our algorithm good performance
3. EWRLS is the best performing online algorithm
  - a. Slowest run time

# Future Improvements

- ▷ Predict solar energy produced
- ▷ Learn seasonal effects
- ▷ Implement algorithm on other datasets
  - HNEI & Weatherboxes





Thanks for listening!