Senior Project Proposal 2102490 Year 2016

Solar irradiance forecasting for Chulalongkorn University location using time series models

Vichaya Layanun ID 5630550721

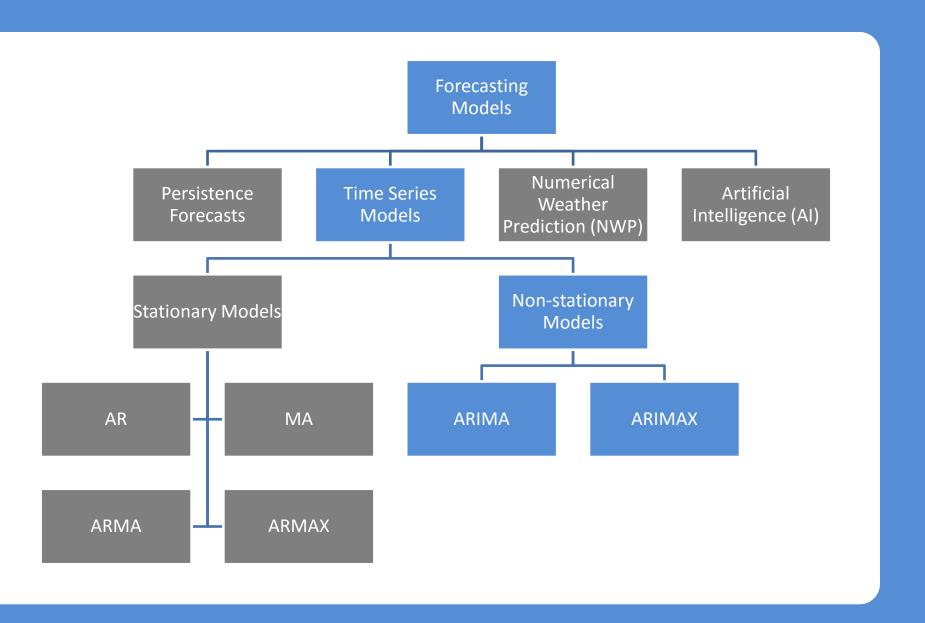
Advisor: Assist. Prof. Jitkomut Songsiri

Department of Electrical Engineering
Faculty of Engineering, Chulalongkorn University

Why solar forecasting is important?

Because, the unreliability of solar power generating has made the entire electrical power generation difficult for power management.

Solar forecasting is a widely-common approach to deal with the problem. An improved accuracy in the forecast can provide a better management of electrical power production.



There are many forecasting models to predict the future solar irradiance. We focus on time series models.

Objective

- To study the relevant variables of solar irradiance forecasting.
- To apply ARIMA models, a Seasonal ARIMA models and ARIMAX models to forecast solar irradiance.
- To validate results of forecasting performance among the models using RMSE, MAE and a sample autocovarince function of the residual as model validation criterion.
- To solve the practical issues on data pre-processing.

Essential Elements

- Relevant variable
- Forecasting Horizon
- Forecasting Performance Evaluation Measures

Relevant Variables

Global Horizontal Irradiance (GHI) is the considered variable which is the geometric sum of Direct Normal Irradiance (DNI) and Diffuse Horizontal Irradiance (DHI).

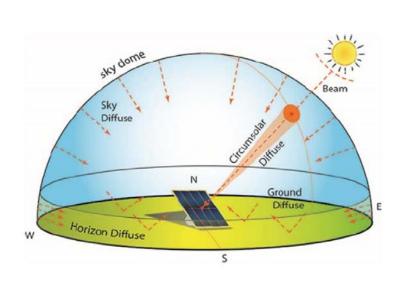


Figure 4: Solar irradiance component

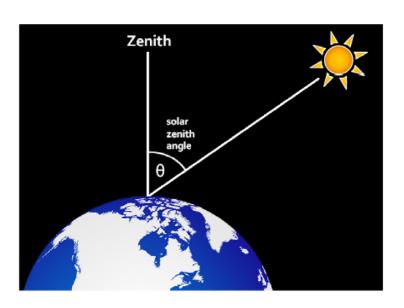


Figure 5: Solar zenith angle

This study predicted GHI and we will use the notation of I(t) throughout this project.

Forecasting Horizon

- To decide how far to do prediction, forecasting horizon is the key. Using time series model for solar forecasting is suitable and widely used for very-short-term forecasting.
- Different forecasting horizons lead to different suitable forecasting method.

Terms of forecasting horizon.

| Forecasting Horizon | Vert-short | Short | Medium | Long |
|------------------------|-------------------|-------------|------------|----------------|
| Time | From a few second | Up to 48-72 | Up to week | Up to month or |
| | to 6 hours | hours ahead | ahead | year |

Forecasting Performance Evaluation Measures

Common evaluation measures are Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE) which are used to validate a forecasting method. RMSE and MAE can be defined as

RMSE =
$$\sqrt{\frac{1}{N} \sum_{t=1}^{N} (I(t) - \hat{I}(t))^2}$$
 (1)

MAE =
$$\frac{1}{N} \sum_{t=1}^{N} |I(t) - \hat{I}(t)|$$
 (2)

where *N* is the length of the time horizon. Desired value of RMSE and MAE is minimized.

Forecasting Performance Evaluation Measures

The residual analysis can also be used for validation. The residuals is defined as

$$e(t) = I(t) - \hat{I}(t) \tag{3}$$

If $\hat{I}(t)$ can capture the dynamic in the true model, then e(t) should behave like white noise. Because we do not know the true model, a sample autocovariance function (ACV) of the residual is determined. ACV of residual is defined as

$$R_e(\tau) = \frac{1}{N} \sum_{t=\tau}^{N} e(t)e(t-\tau). \tag{4}$$

Because ACV of white noise is zero after $\tau > 0$, a desired model is the model of which $R_e(\tau)$ is small for $\tau > 0$.

Time Series Models

- ARIMAX description
- Estimation of integrated term
- Seasonal ARIMA model

ARIMAX description

An autoregressive integrated moving average model with an exogenous input (ARIMAX) is employed to predict the future solar irradiance. The model ARIMAX(p,d,q) is defined by

$$A(q^{-1})(1-q^{-1})^d y(t) = B(q^{-1})u(t) + C(q^{-1})v(t)$$
 (5)

where

$$A(q^{-1}) = I - (a_1q^{-1} + a_2q^{-2} + \dots + a_pq^{-p})$$

$$B(q^{-1}) = B_1q^{-1} + B_2q^{-2} + \dots + B_mq^{-p}$$

$$C(q^{-1}) = I + c_1q^{-1} + c_2q^{-2} + \dots + c_qq^{-p}$$

- q^{-1} is lag operator, y(t) is the solar irradiance (GHI), u(t) are exogenous inputs, v(t) is white noise with zero mean and σ^2 variance.
- In this project, the exogenous inputs consist of the local temperature, relative humidity, wind speed, and air pressure.
- $(1-q^{-1})^d$ is integrated term where d is degree of differencing.

Estimation of integrated term

$$A(q^{-1})y(t) = C(q^{-1})v(t)$$
(6)

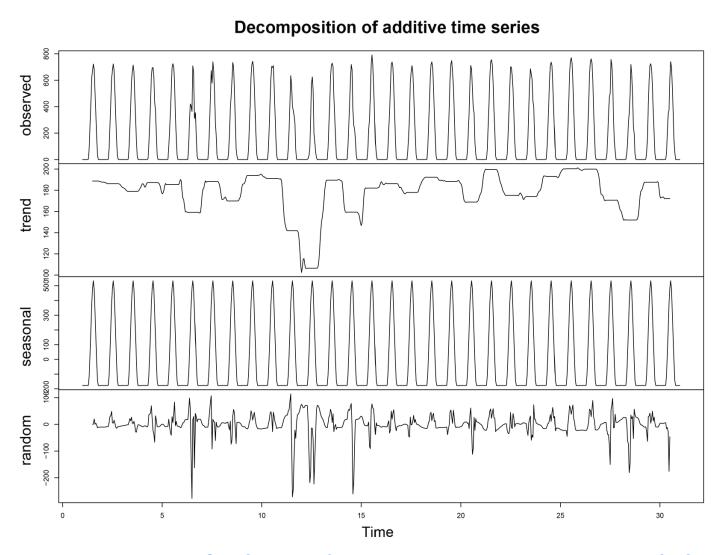
$$A(q^{-1})(1-q^{-1})^d y(t) = C(q^{-1})v(t)$$
(12)

After differencing for certain order, if the resulting ACF behaves similarly to that of a stationary process in the table, then the actual process is ARIMA.

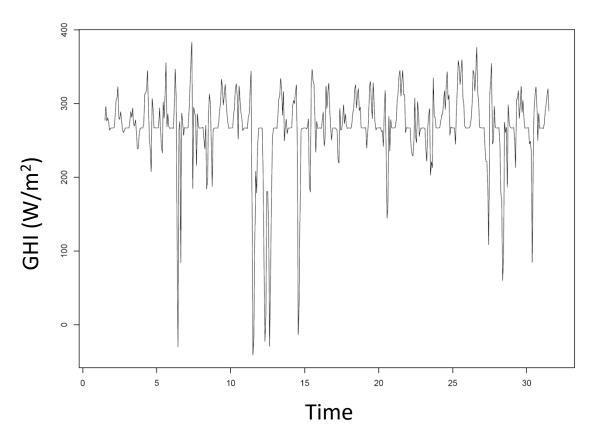
Behavior of the ACF for ARMA Models.

| | AR(p) | MA(q) | ARMA(p,q) | |
|-----|---------------|----------------|---------------|--|
| ACF | Exponentially | Cuts off after | Exponentially | |
| | decay | \logq | decay | |

In other words, if ACF decrease apparently slowly, the transfer function has pole lying near or on unit circle. Hence, the model needs more differencing.



Decomposition of Solar Irradiance in January 2014 in Bangkok.



GHI after removing seasonal trend in January 2014 in Bangkok.

We imply that GHI can be described as ARMA models containing s season:

$$A(q^{-1})y(t) = s(t) + \alpha + C(q^{-1})v(t)$$
 (7)

In this study, we used a seasonal ARIMA models to remove a seasonal trend. The seasonal term and constant are removed by using this transformation. This method is called a Seasonal ARIMA $(p, d, q)(P, D, Q)_T$ models which can be defined as

$$\tilde{A}(q^{-T})A(q^{-1})(1-q^{-T})^{D}(1-q^{-1})^{d}y(t)
= \tilde{C}(q^{-T})C(q^{-1})v(t)$$
(8)

where

$$\tilde{A}(q^{-1}) = I - (\tilde{a}_1 q^{-T} + \tilde{a}_2 q^{-2T} + \dots + \tilde{a}_p q^{-pT})$$

$$\tilde{C}(q^{-1}) = I + \tilde{c}_1 q^{-T} + \tilde{c}_2 q^{-2T} + \dots + \tilde{c}_q q^{-qT}$$

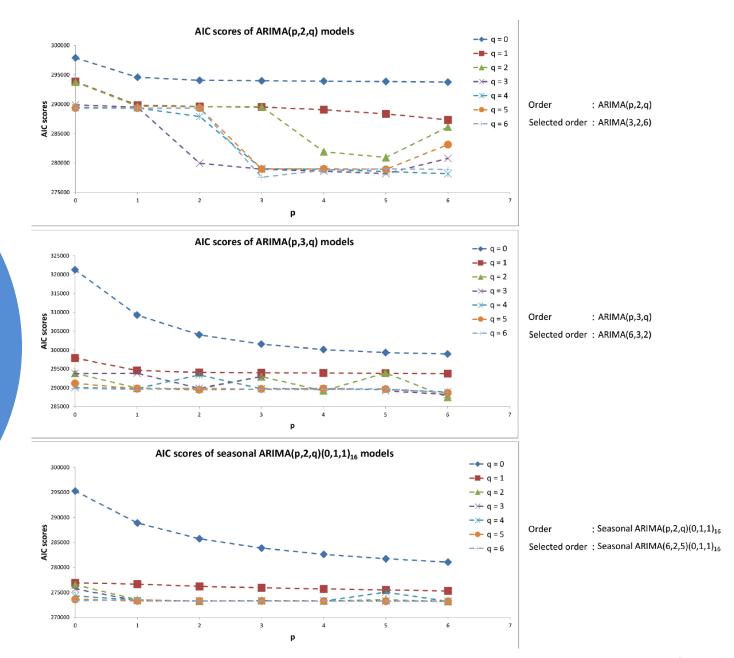
T is a seasonal period and D is integrated seasonal order.

PreliminaryResults

- Model Selection
- Model Validation

Model selection

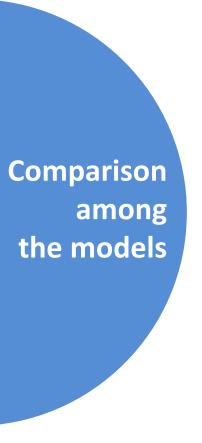
The goal of the experiment is to apply the Akaike information criterion (AIC) and Bayesian information criterion (BIC) to find the optimum order of ARIMA models and Seasonal ARIMA models. AIC and BIC are measures of the performance of the candidate models. The best performance model gives the lowest AIC or BIC.

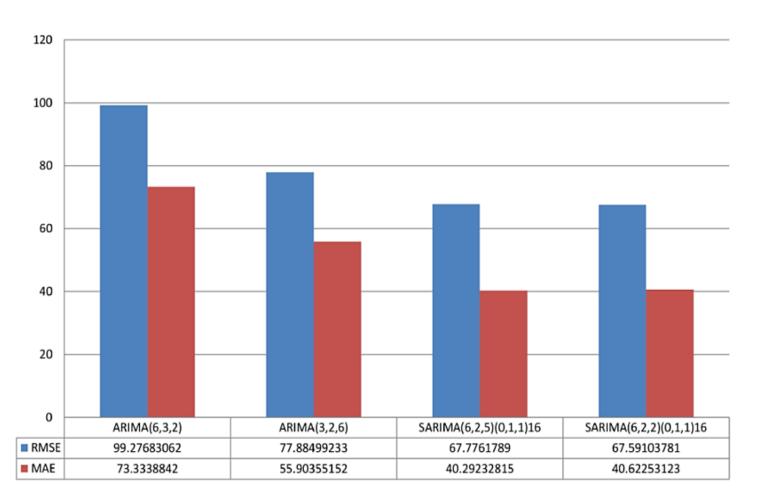


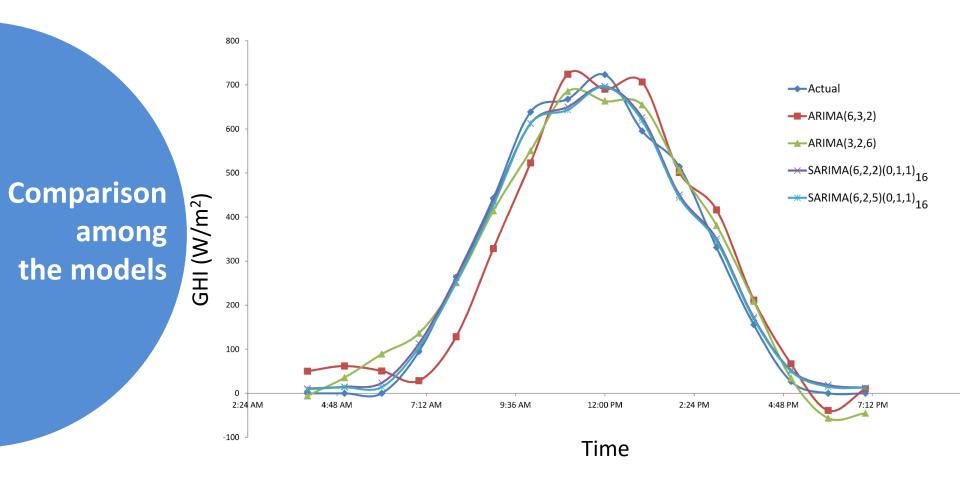
AIC scores of the candidate models

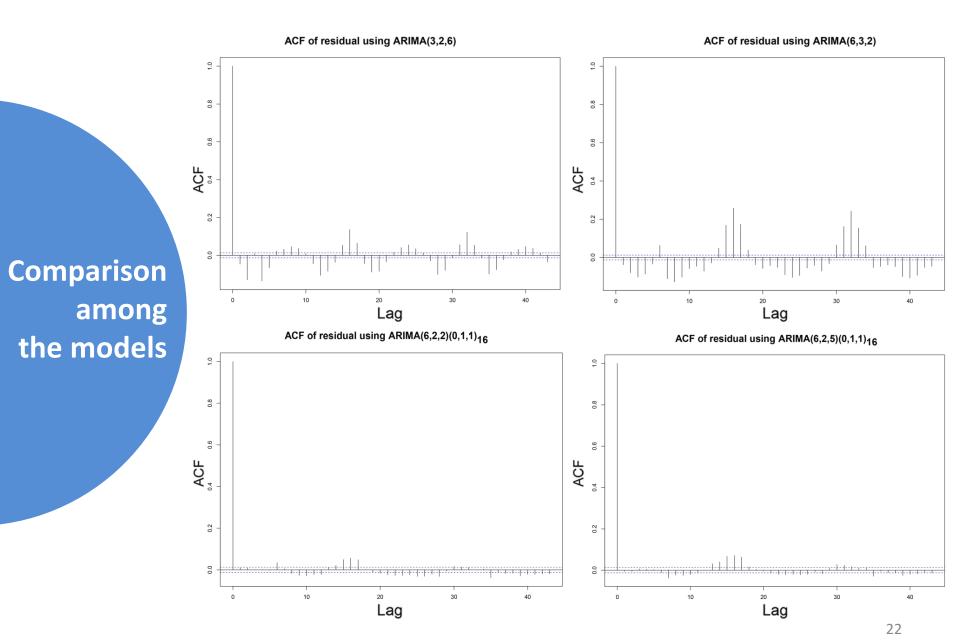
Model validation

After we select the order of the candidate models, we would compare their performance on the unseen data sets. We used RMSE and MAE to validate the performance of the candidate models. The validation data is historical GHI data in year 2015.









Project overview

- Scope of work
- Expected outcomes

Scope of work

- We focus on solar irradiance in the area of Chulalongkorn University location by using ARIMAX and seasonal ARIMAX models.
- The exogenous inputs consist of the local temperature, relative humidity, wind speed and air pressure will be included in the models.
- We will conduct experiments to verify our approach by using data obtained from Thai Meteorological Department (TMD).
- We will conduct an experiment by using data obtained from department of electrical engineering if they are available.
- We will study the consequence of seasons of the year in the location.

Expected outcomes

- Comparison results of forecasting performance among
 Persistence forecast, ARIMA models, a Seasonal ARIMA models
 and ARIMAX models using Root Mean Squared Error (RMSE),
 Mean Absolute Error and a sample autocovariance function (ACV)
 of the residual as model validation criterion.
- Schemes for solving practical issues on data pre-processing which are 1) missing data and 2) timely asynchronous data.



Backup

Relevant Variables

Global Horizontal Irradiance (GHI) is the considered variable which is the geometric sum of Direct Normal Irradiance (DNI) and Diffuse Horizontal Irradiance (DHI).

$$GHI = DHI + DNI \cos(\theta)$$
 (9)

where θ is the solar zenith angle. The unit of GHI, DNI and DHI are W/m^2 . This study predicted GHI and we will use the notation of I(t) throughout this project.

Persistence Forecasts

Persistence forecast as a baseline prediction method is used for a comparison to more advanced methods. There are many equations of persistence forecast in accordance with each study.

$$\hat{I}(t+h) = I(t) \tag{10}$$

1) Persistence model supposes that solar irradiance at time t + h can be predicted by it value at time t.

Persistence Forecasts

2) Clearness persistence forecast supposes that clearness index is constant, i.e.

$$K(t+h) = K(t),$$

where clearness index is defined as:

$$K(t) = \frac{I(t)}{I_{\text{EX}}(t)}.$$
 (11)

 $I_{\rm EX}(t) = I_0 \cos\theta(t)$ where I_0 is an average value of the extraterrestrial irradiance and is suggested to be 1360 and $\theta(t)$ is solar zenith angle at time t. Thus,

$$\hat{I}(t+h) = K(t)I_{\text{EX}}(t+h) \tag{12}$$

Persistence Forecasts

2) Clear sky persistence forecast supposes that clear sky index is constant, i.e.

$$k(t+h) = k(t),$$

where clearness index is defined as:

$$k(t) = \frac{I(t)}{I_{\rm clr}(t)}. (13)$$

 $I_{\rm clr}(t)$ is the value from a clear sky irradiance model at time t which can be widely estimated by Ineichen model. Thus,

$$\hat{I}(t+h) = k(t)I_{clr}(t+h) \tag{14}$$

An estimate of the daily seasonal effect $\hat{s}(t)$ can be obtained by averaging $\tilde{s}(t)$ which is obtained by subtracting $\hat{m}(t)$:

$$\hat{s}(t) = \frac{1}{N+1} \sum_{k=0}^{N} \tilde{s}(t+kT)$$

where T is the seasonal period,

$$\tilde{s}(t) = y(t) - \hat{m}(t)$$

$$\widehat{m}(t) = \frac{\frac{1}{2}y\left(t - \frac{T}{2}\right) + y\left(t - \frac{T}{2} + 1\right) + \dots + y\left(t + \frac{T}{2} - 1\right) + \frac{1}{2}y\left(t + \frac{T}{2}\right)}{T}$$

In this study, we used a seasonal ARIMA models to remove a seasonal trend. Giving the following equation as an example:

$$y(t) = s(t) + \alpha + v(t) \tag{15}$$

where s(t) = s(t - kT), k is an integer and α is a constant.

We subtract y(t) by y(t - T).

$$y(t) - y(t - T) = s(t) + \alpha + v(t) - s(t - T) - \alpha$$
$$-v(t - T)$$
$$y(t) - y(t - T) = v(t) - v(t - T)$$

Model Selection

The AIC is defined as

$$AIC = 2L + 2d \tag{16}$$

where L is the loglikelyhood function and d is the number of effective parameters.

The BIC is defined as

$$BIC = 2L + d\log N \tag{17}$$

where *N* is the number of sample.

Autocorrelation Function

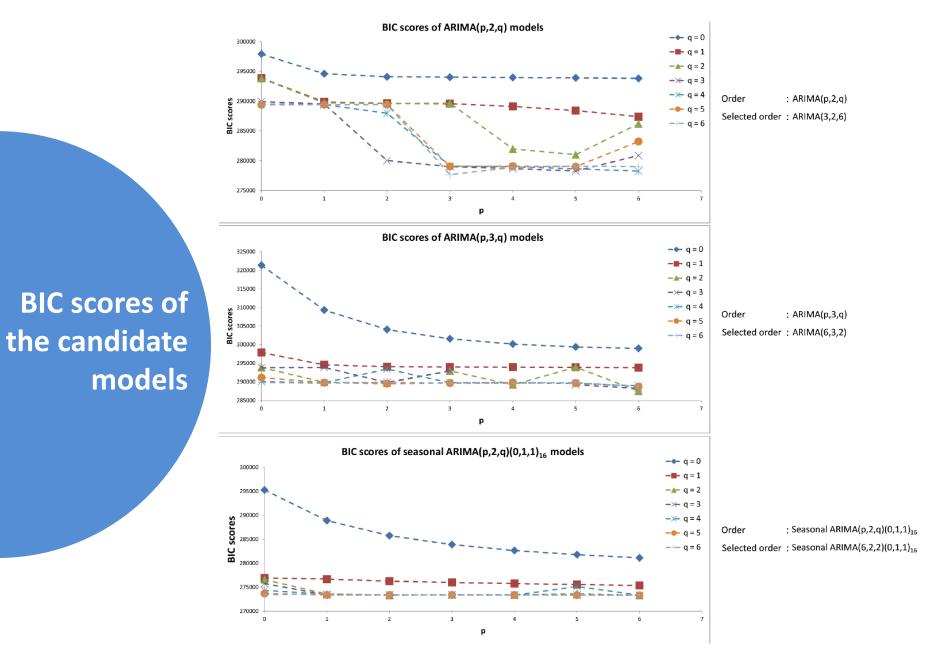
An autocorrelation function is defined by

$$ACF = \frac{R(\tau)}{R(0)} \tag{18}$$

where the sample autocovariance function (ACVF) is defined by

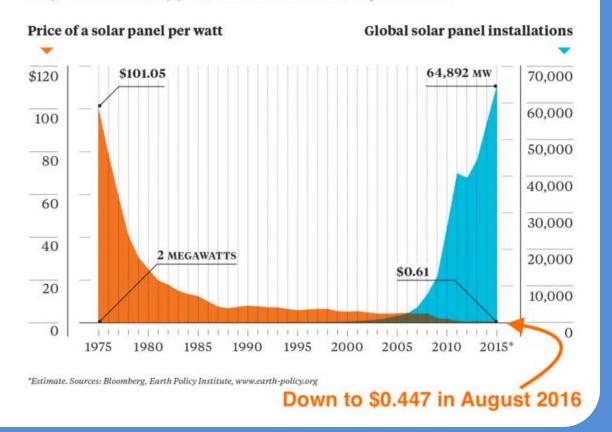
$$R(\tau) = \frac{1}{N} \sum_{t=\tau}^{N} y(t) y(t-\tau)$$
 (19)

where the expectation of y is zero and the variance of y which are the same at all time t.



Solar on Fire

As prices have dropped, installations have skyrocketed.



The price of a solar panel have obviously dropped from \$101.05 in 1975 to \$0.447 in 2016 and global solar panel installations have risen from 2 MW in 1975 to 64,892 MW in 2015.

Total installed renewable power plant capacity from AEDP 2015-2036 in Thailand.

| Alternative Energy Development Plan during 2015-2036 (MW) | | | | | | | | | |
|---|---------|-------|---------|-------|---------|--------|--------------|----------|--|
| Year | Solar | Wind | Hydro | Waste | Biomass | Biogas | Energy crops | Total | |
| 2014 | 1,298.5 | 224.5 | 3,048.4 | 65.7 | 2,541.8 | 311.5 | - | 7,490.4 | |
| 2036 | 6,000 | 3,002 | 3,282.4 | 500 | 5,570 | 600 | 680 | 19,634.4 | |

Source : Thailand Ministry of Energy