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## Forecasting power output of PV grid connected system in Thailand without using solar radiation measurement

Charnon Chupong and Boonyang Plangklang

*Department of Electrical Engineering, Faculty of Engineering, Rajamangala University of Technology Thanyaburi, 39 M.1 Klong 6, Thanyaburi, Pathumthani 12110, Thailand*

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### Abstract

PV systems have been increasingly installed worldwide in recent years. Because it produces clean energy, moreover the development of technology is continued therefore the reliability is increasing and the price is decreasing in opposite. To implement the PV system, however, a significant limitation of PV system is the uncertainty of power from the sun. This will affect the quality of the electrical system that connected. Therefore, this article will present the power forecasting of a PV system by calculating the solar radiation, collecting data from weather forecasting, and using Elman neural network to forecast by using data from PV system installed at roof top of Faculty Science and Technology Rajamangala University of Technology Thanyaburi. The results of study found that the tendency to apply this method any further

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Keyword: Neural network; PV power forecasting; Solar radiation

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### 1. Introduction

PV systems have been increasingly installed worldwide in recent years. Because it produces clean energy, moreover the development of technology is continued therefore the reliability is increasing and the price is decreasing in opposite. To implement the PV system, however, a significant limitation of PV system is the uncertainty of power from the sun. This will affect the quality of the electrical system that connected [1].

Therefore, the forecasting power output of the PV system can help to increase the quality of the power system. There are some researches discuss about the forecasting of solar radiation [2] [3], but is not sufficient to forecast the power output of PV systems because power output of PV systems also depend on

the temperature changes as well. And some researches discuss the forecasting power output of the PV system that need to be installed solar radiation measurement [4].

In this article will present the forecasting power output of PV grid connected system without using solar radiation measurement. The methodology used is to calculating the hourly solar radiation for the next day and use data from weather forecasting maximum temperature, minimum temperature and cloud conditions in the next day as input of neural network. To forecast hourly power output of PV system [5].

## 2. Theoretical Background

### 2.1. Calculation of solar radiation on any plane

Solar radiation on any plane consist of 3 components as Equation 1

$$G_t = G_b + G_d + G_r \quad (1)$$

where  $G_t$  is the total radiation ( $W/m^2$ ),  $G_b$  the direct radiation ( $W/m^2$ ),  $G_d$  the diffuse radiation ( $W/m^2$ ), and  $G_r$  the reflect radiation ( $W/m^2$ ).

All 3 components can be calculated by Eqs. (2.1)-(2.3)

$$G_b = G_o \cos \theta_s \quad (2.1)$$

$$G_d = G_o \cos \theta_z \quad t_d \frac{(1 + \cos \beta)}{2} \quad (2.2)$$

$$G_r = \rho G_o \cos \theta_z \quad t_r \frac{(1 + \cos \beta)}{2} \quad (2.3)$$

Here,  $G_o$  is the solar radiation outside the earth atmosphere ( $W/m^2$ ), which changes every day during the year due to the motion of the earth around the sun, calculated from Eq. (3).

$$G_o = G_s \left[ 1 + 0.033 \cos \left( 360 \frac{D}{365} \right) \right] \quad (3)$$

where  $G_s$  denotes the solar constant  $1367 W/m^2$ ,  $D$  the day in year (1-365),  $t_b$ ,  $t_d$ ,  $t_r$  the atmospheric transmittance for direct radiation, diffuse radiation, and reflected radiation, respectively that calculated as Eqs. (4)-(7) [5], and  $\rho$  the reflectance value of ground.

$$t_b = a_0 + a_1 e^{\left( -\frac{k}{\cos \theta_z} \right)} \quad (4)$$

where

$$a_0 = r_0 [0.4237 - 0.0082(6 - A)^2] \quad (5.1)$$

$$a_1 = r_1 [0.5055 - 0.00595(6.5 - A)^2] \quad (5.2)$$

$$k = r_2 [0.2711 + 0.01858(2.5 - A)^2] \quad (5.3)$$

$$t_d = 0.271 - 0.294 t_b \quad (6)$$

$$t_r = 0.271 + 0.706 t_b \quad (7)$$

where  $A$  is the attitude of location in km,  $r_0$ ,  $r_1$  and  $r_k$  the correction factor for various climate types, respectively as table 1

Table 1. Correction factor for various climate type.

Climate type	$r_0$	$r_1$	$r_k$
Tropical	0.95	0.98	1.02
Midlatitude Summer	0.97	0.99	1.02
Subarctic Summer	0.99	0.99	1.01
Midlatitude Winter	1.03	1.01	1.00

From Eq. (2)  $\theta_z$  is zenith angle and  $\theta_s$  is incident angle calculated by Eqs. (8) and (9) and  $\beta$  is inclination angle of PV surface, the details of angles are shown in Fig. 1.

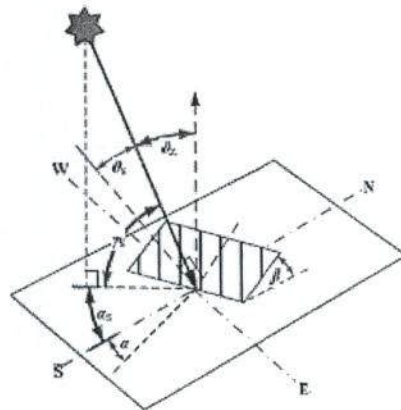


Fig. 1. Zenith Angle, Incident Angle and Inclination Angle.

$$\cos \theta_z = \cos \delta \cos \phi \cos \omega + \sin \delta \sin \phi \quad (8)$$

$$\cos \theta_s = \sin \delta \sin \phi \cos \beta - \sin \delta \cos \phi \sin \beta \cos \alpha + \cos \delta \cos \phi \cos \beta \cos \omega + \cos \delta \sin \alpha \sin \omega \sin \beta + \cos \delta \sin \phi \sin \beta \cos \alpha \cos \omega \quad (9)$$

where

$\delta$  is declination angle,

$\phi$  is latitude of location,

$\omega$  is hour angle of the sun equal 0 in noon, +90° when sunrise -90° when sunset change

150 every 1 hour [6],

$\alpha$  is azimuth angle.

$$\delta = 23.45 \sin \left[ 360 \frac{(D + 284)}{365} \right] \quad (10)$$

$$\omega = 15(12 - ST) \quad (11)$$

where

$$ST = LST + 4(Ls - Lloc) + Et \quad (12)$$

ST is sun time (hour, minute),

LST is local standard time (hour, minute),

Ls is reference longitude (for define time zone, i.e. 1050 for Thailand),

Lloc is longitude for site location,

Et is equation of time (minute).

$$Et = 229.1831(0.000075 + 0.001868\cos\theta - 0.032077\sin\theta - 0.014615\cos 2\theta - 0.040849\sin 2\theta) \quad (13)$$

where

$$\theta = 360 \frac{(D-1)}{365} \quad (14)$$

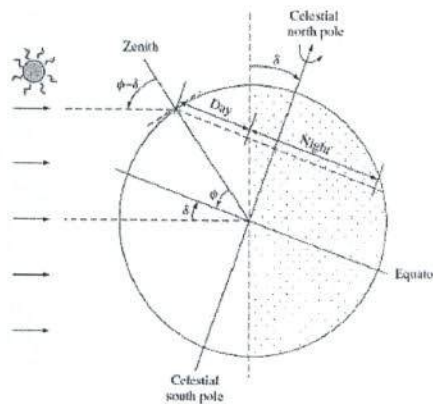


Fig. 2. Declination Angle and Zenith Angle.

Eqs. (1)-(14) used for calculating solar radiation on any surface in anytime of year in clear sky without cloud only [5]. In forecasting PV power output application, the other weather conditions are also considered as temperature and cloudy.

## 2.2. Recurrent Artificial Neural Network

The Elman network commonly is a two-layer network with feedback from the first-layer output to the first-layer input. This recurrent connection allows the Elman network to both detect and generate time-varying patterns. A two-layer Elman network is shown in Fig. 3.

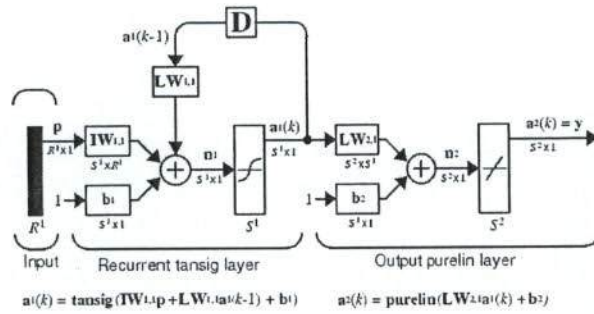


Fig. 3. Elman Network.

### 3. Proposed Forecasting Method

Proposed forecasting method presented in this article is to use Elman neural networks which the inputs for network has 14 inputs including the solar radiation from 7:00 to 17:00 for the next day, which was calculated in Section 2.1 (11 inputs) and other 3 inputs are data from weather forecast the highest temperature for next day, the lowest temperature for next day and cloudy condition for next day that use cloudy index as Table 2

Table 2. Cloudy index.

Cloudy condition	Cloudy index
Clear,Partly-Cloudy	0.9
Cloudy	0.6
Rain,Fog	0.3

And Outputs from network are forecast hourly power output (kW) from PV from 7:00 to 17:00

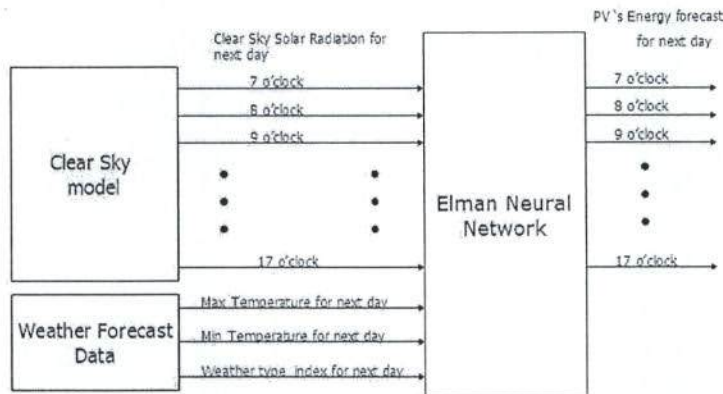


Fig. 4. Diagram of propose forecasting method.

## 4. Experiment and Results

### 4.1. Training the network

In this experiment using the MATLAB software to create network and training, data used to train the network come from the calculation in Section 2.1, weather forecast website [www.wunderground.com](http://www.wunderground.com) and hourly data of output PV 1 kWp Grid Connected System at roof-top of Building Faculty of Science and Technology, Rajamangala University of Technology Thanyaburi. In this training use these data from 17<sup>th</sup> Jan 2011 to 23<sup>rd</sup> Jan 2011

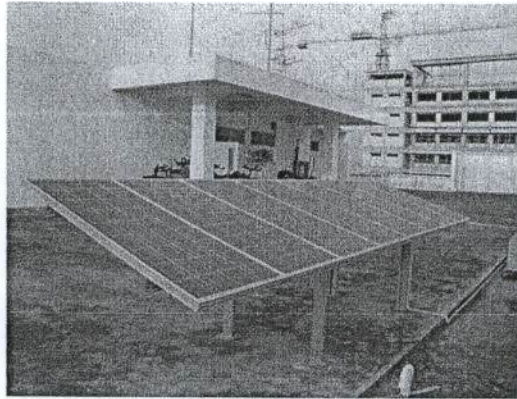


Fig. 5. PV Grid Connected System used in this article.

These data are taken through a pre-processing by Linear model in the MATLAB to normalize all data in range [-1 1] that make more efficiency in training process.

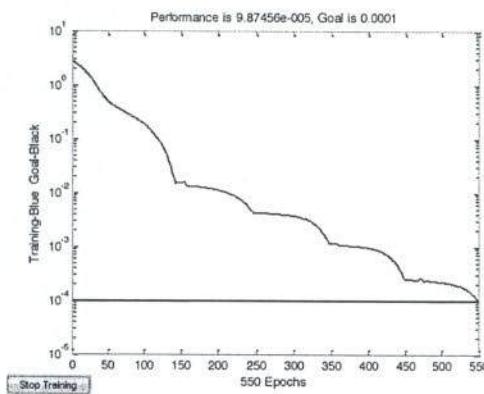


Fig. 6. Training of Elman Neural Network.

#### 4.2. Experiment Results

After training the network, we have another set of data to test the network. These data come from calculation of the solar radiation and weather forecast during 31 January to 3 February 2011. We normalize these data by pre-processing process and then input to network. Now network gives output in range [-1 1] then we input these data to post-processing by the linear model in MATLAB and finally we can get forecast values. These forecast values are compared with the actual values recorded at site. Then calculated as the mean absolute percentage error (MAPE) by equation 15, which in this experiment, the MAPE is equal to 16.83%.

$$MAPE = \frac{100}{N} \sum_{i=1}^N \frac{|P_f^i - P_a^i|}{P_a^i} \% \quad (15)$$

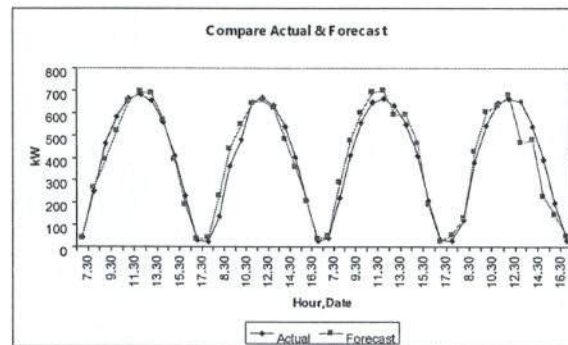


Fig. 7. Compare Forecast value and Actual value.

To validate this result we compare this MAPE 16.83% with application of Recurrent Neural Network and measured data of solar radiation to forecast PV power output [4] that have MAPE about 12% -17% vary in each month. The MAPE of 2 methods are very close that mean this forecasting method can acceptable.

## 5. Conclusion

Forecasting power output of PV Grid Connected System by data from calculating the solar radiation in clear sky condition and weather forecast data as input to the Elman neural network instead of using a solar radiation measurement. In this experiment found that the forecast and actual values go in the same direction. The errors were 16.83% the data used in this study were also few and still have to collect more data to study in further.

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