

## PV Power Forecasting with Holt-Winters Method

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### Abstract

Due to global warming issue and growing of energy demand, photovoltaic (PV) power plant is a desirable alternative to electrical power generations. An accurate PV power forecasting is essential to alleviate its negative impacts and to improve its performance. This paper proposed a short-term PV power forecasting technique based on Holt-Winters method. Its property and principle are presented. There are two main parameters, i.e. the number of days ( $N$ ) and the weight index ( $\alpha$ ). The values of these two parameters affect the forecasting accuracy, and a set of optimal values for both parameters used for all season is proposed. A real PV generated power profile is collected from the eastern part of Thailand and used in this study. The performance of the proposed forecasting technique is carried out by MATLAB program. The simulation results indicate that the proposed method provides acceptable short-term forecasting results. The proposed technique can be applied in energy management and electrical power smoothing applications.

**KEY WORDS:** PV Power Forecasting, Holt-Winters Method Forecasting, Renewable Energy, Photovoltaic Power System

### 1. INTRODUCTION

For decades, global warming and fossil fuel reduction boost renewable energy to be a feasible resource for electric power generations. Beside non-carbon emission, in Thailand, renewable energy

contributes to sustainable domestic electric power generation and reduce energy imports.

Because of its clean, safe, non-moving parts and higher system efficiency, photovoltaic power plants are a desirable choice in recent electric power generation worldwide. According to measured solar irradiance, Thailand has great potential to apply solar energy in electrical power generations. Due to the increasing of energy demand, Thai government targets electric power generated by solar energy up to 15.5 GW in 2037, according to Thailand Alternative Energy Development Plan (AEDP 2018).

However, the main challenge of the PV power plants is its highly sensitive on uncontrollable solar irradiance and climate conditions. Unstable power output will cause voltage fluctuations at the point of common coupling and its nearby feeders. Without being mitigated, it will negatively affect power quality of the grid [1],[2]. As results, there will be some limitation in utilizing PV power plants. To enhance the effectiveness of PV generation, accurate forecasting of PV power output is necessary to approximate upcoming PV generated power. Energy management systems and power smoothing with energy storage system are example applications of PV power forecasting [3]-[5].

PV generated power forecasting method in this research derives from a time series statistical forecasting technique named “Holts-Winters”, which employs historical data and designated parameters to predict the results.

This research focuses on short-term PV power forecasting. Selection of suitable parameters and the number of data on each forecasted season will be proposed. By using MATLAB, forecasting results and performance of the proposed forecasting technique will be validated. Section 2 will introduce techniques used for PV power forecasting. The proposed forecasting method and the performance evaluation are demonstrated in Section 3. The simulation results will be carried out and discussed in Section 4.

## 2. FORECASTING TECHNIQUES

### 2.1 Literature Review on Forecasting Method

Up to date, various PV power generation forecasting techniques has been proposed. Those include artificial neural network (ANN) [6], fuzzy logic [7], stacking-support vector machine (stacking-SVM) [8] and seasonal autoregressive integrated moving average (SARIMA) [9].

In [6], an artificial neural network (ANN) model is developed based on beam irradiance, diffuse irradiance, plane of array irradiance, ambient temperature, wind speed, cell temperature and relative humidity for 1-day ahead hourly forecasting of PV power outputs. ANN method, however, needs user to specify all necessary model parameters, which obtain from trial-and-error and relate to results.

PV power is forecasted using fuzzy logic in [7] with humidity and amount of cloud as input parameters. Fuzzy logic cannot directly learn from previous data, and its forecasting accuracy is increased by forecasted value correction.

In [8], stacking-SVM is proposed for short-term PV power forecast. SVM is a machine learning technique, which has many parameters and needs high computation power. In [9], SARIMA is applied to forecast very short-term PV power. Its limitation is how to choose its best parameters.

Compared with previous techniques, Holt-Winters method shows some feasibility if employed in PV power forecasting.

### 2.2 Holt-Winters Method Forecasting

This research applies another statistical forecasting technique called Holt-Winters forecasting method or Triple Exponential Smoothing Method to forecast PV output power. Previously, Holt-Winters forecasting method has been applied in many applications, such as short-term load forecasting or mobile network traffic prediction [10]-[11]. Holt-Winters forecasting method comprises of three main components: series, trend and season. The forecasting procedure can be expressed as follows:

The series component can be determined by

$$S(t) = \frac{\alpha \times D(t)}{c(t-p)} + (1 - \alpha) \times (S(t-1) + T(t-1)), \quad (1)$$

the trend component can be calculated by

$$T(t) = \beta \times (S(t) - S(t-1)) + (1 - \beta) \times T(t-1) \quad (2)$$

and the seasonal component can be determined by

$$C(t) = \frac{\gamma \times D(t)}{S(t)} + (1 - \gamma) \times c(t-p). \quad (3)$$

Then, a forecasted value for a period of  $y$  for a specific data can be calculated be the following formula:

$$F(t, t+y) = (S(t) + T(t) \times y) \times c(t+y-p) \quad (4)$$

Where

- $S$  is series estimate (vary on the amount of  $\alpha$ ),
- $T$  is trend estimate (vary on the amount of  $\beta$ ),
- $c$  is seasonality estimate (vary on the amount of  $\gamma$ ),
- $p$  is seasonal period,
- $y$  is a number of data,
- $D$  is the actual data and
- $F$  is forecasted value for the coming period.

## 3. PROPOSED PV POWER FORECASTING

In this section, the proposed PV power forecasting technique based on Holt-Winters method will be presented. From previous research, this method indicated possibility to be applied in PV power forecast. With Holt-Winters method, PV profile

fluctuation, series and seasonal components are required to effectively forecast PV power generation.

The proposed algorithm is shown in Fig. 1, where  $t$  is time-of-day and the weight index,  $\alpha$ , is in the range of 0 to 1.

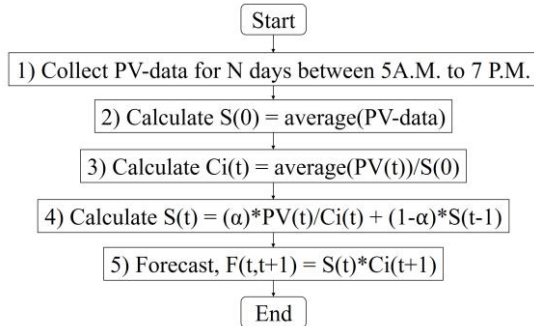


Figure 1. Block diagram of the proposed forecasting algorithm.

## 4. SIMULATION RESULT

### 4.1 Simulation Cases

The proposed forecasting method is used for short-term PV power output prediction. The historical PV power data with 15-minute interval as shown in Fig. 2, collected between Januarys to June in 2019 in the eastern part of Thailand, is used in this study.

From Fig. 2, the studied PV profile is categorized into three patterns according to seasons: 1) winter 2) summer and 3) rainy. PV profile, in the winter and the summer might fluctuate because of cloud passing but not drop abruptly. However, solar irradiance in summer is more intense than the winter. In the rainy, PV characteristic is hard to predict, because sometimes it had rain during the day. All PV generated power data is set up to percentile.

The number of days ( $N$ ) and the weight index ( $\alpha$ ) are the main parameters to be selected. The weight index is the constant forecasting parameter and is between 0-1. The goal of this research is to find the suitable values for each parameter to achieve the best forecasting performance.

The proposed forecasting method is simulated and verified by MATLAB R2018b. The result of the proposed forecasting method will be presented in the following section.

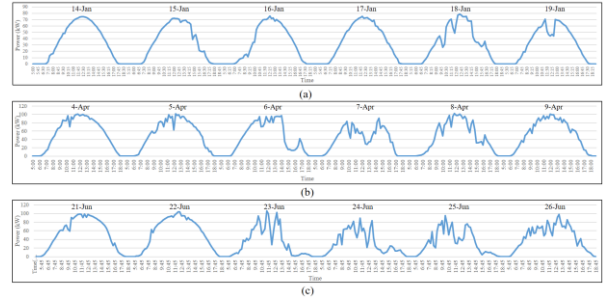


Figure 2. An example of the measured PV profiles used in the study in (a) winter (b) summer (c) rainy seasons

### 4.2 Forecasting Error

To verify the performance of the proposed forecasting technique compared to the previous techniques, forecasting error can be employed. There are various tools used to evaluate the forecasting error. This research utilizes the following evaluation indices presented in [12] to evaluate the forecasting errors:

- Mean Relative Error

$$MRE = \frac{1}{N} \sum_{i=1}^N \frac{|P_{forecast(i)} - P_{actual(i)}|}{P_{cap}} \times 100\% \quad (5)$$

- Root Mean Square Error

$$RMSE = \sqrt{\frac{\sum_{i=1}^N (P_{forecast(i)} - P_{actual(i)})^2}{N}} \quad (6)$$

Where

$P_{forecast}$  is forecasting value.

$P_{actual}$  is the actual value.

$P_{cap}$  is the PV power capacity.

$N$  is number of considered time interval.

Based on MRE, lower value indicates that the obtained result is closer to actual value. This index is quite meaningful, because it shows how much relative difference with respect to the PV power capacity.

RMSE will give bigger weight to the large error. It is obtained by average magnitude of the forecasting errors. RMSE, therefore, does not provide percentile evaluation indices suitable to compare with other results.

### 4.3 Key Results

The goal is to determine the suitable values for the number of days ( $N$ ) and the weight index ( $\alpha$ ) in each season. The results of the forecasting PV generated power based on three seasons with 2 samples from each season, are shown in Fig. 3-5. The forecasting error results is shown in Table 1 to 3.

An example of the error evaluation for PV power forecasting on 6 February 2019 is shown in Table 1 and plotted in Fig. 3(b). Although, different  $\alpha$  values is employed, MRE and RMSE result are very similar. At  $N = 3$ , error is higher than others, because the past data showed some fluctuation which influenced its forecasted result. This indicates if the historical data are similar, better forecasting performance will be achieved.

Historical PV generating power, becoming  $C_i$  parameter, will influence the forecast result as shown in Fig. 4(a). Although, the considered PV profile is smooth, the results likely fluctuates. If the previous data is fluctuated,  $C_i$  then becomes fluctuate too. See Table II, compared with  $N = 3$ , errors in case of  $N = 15$  are reduced significantly because of fluctuated  $C_i$  as previously mentioned.

Then  $\alpha$ , which affects to series level ( $S$ ), will be considered. The weight index is a factor to control the weight between recent data and historical data. In Fig. 3(a),  $\alpha = 0.2$  and  $\alpha = 0.5$  are compared. On cloudy or rainy day, using high  $\alpha$  value will make forecast more accurate. The result in Table 3 is confirmed this relationship.

Moreover, Table III presents that the higher  $\alpha$  value, the more accurate forecasting results, while there is no affect with different  $N$ . From the simulation results, for fluctuated PV power generation, many data is not necessary. In contrast, more data affects to higher result accuracy, and higher  $\alpha$  value barely influences better forecasted results.

Table 1. MRE/RMSE of winter season samples

Alpha	MRE (%) / RMSE (kW)					
	$N = 3 \text{ days}$		$N = 5 \text{ days}$		$N = 15 \text{ days}$	
0.2	3.444	5.534	2.879	4.652	2.507	4.005
0.4	3.529	5.706	2.895	4.671	2.588	4.162
0.6	3.575	6.005	2.994	4.881	2.755	4.394
0.8	3.717	6.469	3.202	5.255	2.938	4.715

Table 2. MRE/RMSE of summer season samples

Alpha	MRE (%) / RMSE (kW)					
	$N = 3 \text{ days}$		$N = 5 \text{ days}$		$N = 15 \text{ days}$	
0.2	7.818	10.595	6.344	8.728	4.296	5.966
0.4	6.852	9.320	5.615	7.616	3.598	5.436
0.6	6.506	9.000	5.211	7.308	3.438	5.346
0.8	6.665	9.272	5.137	7.471	3.706	5.519

Table 3. MRE/RMSE of rainy season samples

Alpha	MRE (%) / RMSE (kW)					
	$N = 3 \text{ days}$		$N = 5 \text{ days}$		$N = 15 \text{ days}$	
0.2	5.885	9.518	5.796	9.319	5.731	9.315
0.4	4.603	7.758	4.511	7.666	4.362	7.399
0.6	4.131	7.394	4.024	7.240	3.859	6.783
0.8	3.838	7.465	3.695	7.213	3.578	6.609

### 4.4 Performance Comparison

The performance comparison of the proposed method and SARIMA model is carried out. SARIMA model is the time-series forecasting method [9]. Its equation can be expressed in (7).

$$\text{SARIMA } (p,d,q)(P,D,Q)_s \text{ model:} \\ (1 - \phi_1 B - \dots - \phi_p B^p)(1 - \Phi_1 B^s - \dots - \Phi_P B^{Ps})(1 - B)^d (1 - B^s)^D Y_t = c + (1 + \theta_1 B + \dots + \theta_q B^q)(1 + \Theta_1 B^s + \dots + \Theta_Q B^{Qs}) e_t \quad (7)$$

Where

$d$  is number of difference time,

$D$  is seasonal difference,

$\phi$  is autoregressive coefficients,

$\theta$  is moving average coefficients,

$c$  is constant,  
 $e_t$  is white noise,  
 $Y_t$  is forecasted values and  
 $B$  is backshift operator.

The performance evaluation of both model is presented in Table IV and Fig. 7. From the simulation results, the proposed method has a slightly better results. The weak point of SARIMA model is parameter choosing.

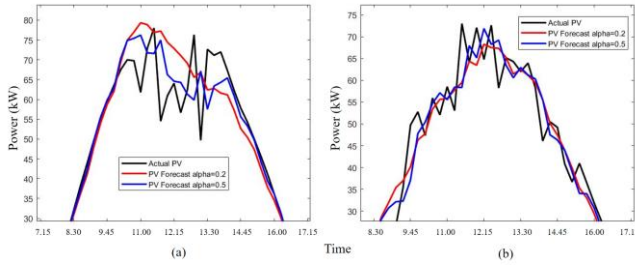


Figure 3. Forecasting result of winter (a) 26-Jan (b) 6-Feb

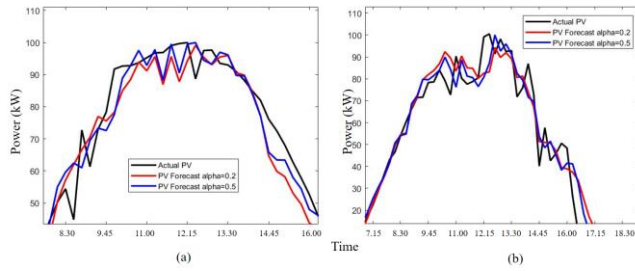


Figure 4. Forecasting result of summer (a) 16-Apr (b) 24-Apr

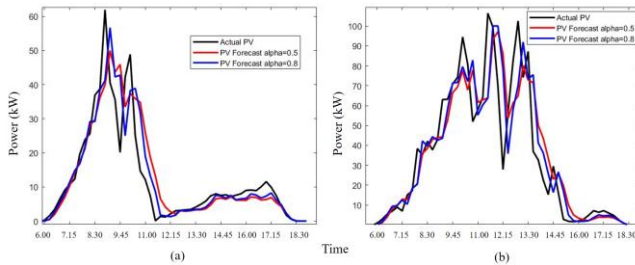


Figure 5. Forecasting result of rainy season (a) 17-Jun (b) 23-Jul

In conclusion of choosing both parameters, evaluated based on MRE and RMSE results, the optimal number of data  $N$  and  $\alpha$  for each month are chosen and shown in Fig. 6. Then, the sample forecasting results is shown in Fig. 9.

The proposed forecasting method is developed for 15-minutes ahead forecasting. However, in some circumstances, longer PV power forecasting such as 24-hour ahead could be useful. So, we apply the proposed technique to forecast 1-day ahead PV output power. The results after using the proposed method for 1-day ahead compared with 15-min ahead are shown in Fig. 8 and Table 5. From the

results, the proposed technique can predict 1-day ahead PV power with some error. These error will negatively affect to some application, which is sensitive to forecasting accuracy. Power smoothing, for example, applies generated power transfer commands based on forecasting results to manage its energy storage's state of charge. Higher error in 1-day forecasting compared with 15-min one is expected. A study to improve the proposed technique for further forecasting is ongoing. Additional data, for example weather forecast, may improve the forecasting accuracy.

TABLE 4. MRE/RMSE OF SARIMA AND PROPOSED MODEL

Date	30-May		24-Jun	
Model	SARIMA	Proposed	SARIMA	Proposed
MRE (%)	9.9052	8.5643	6.682	5.917
RMSE (kW)	14.7045	13.2922	10.4035	9.8615

TABLE 5. MRE/RMSE OF 1-DAY AND 15-MIN AHEAD FORECASTING

Date	MRE (%) /RMSE (kW)			
	1-day		15-min	
7-Feb	7.79	13.23	5.24	8.72
16-Apr	9.50	12.17	3.16	5.08
21-Jun	19.02	25.49	7.54	10.47

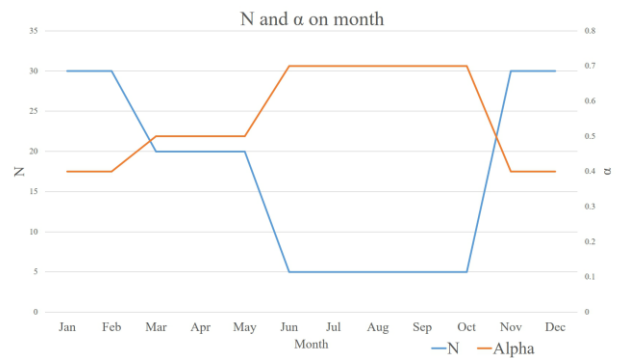


Figure 6. Summary of parameter choosing for each month

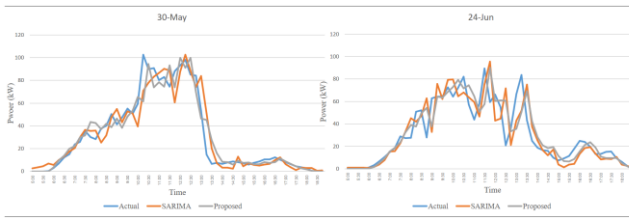


Figure 7. Forecasting result of SARIMA and proposed model

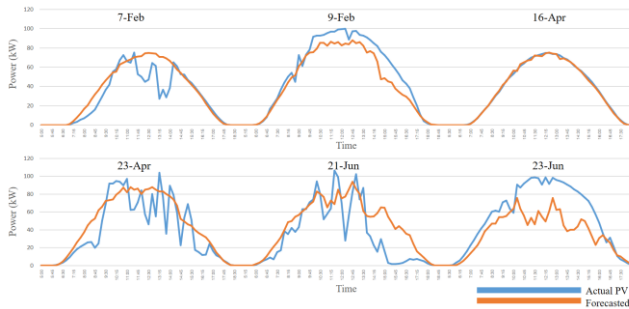


Figure 8. 1-Day ahead PV forecasting compared with actual PV generation

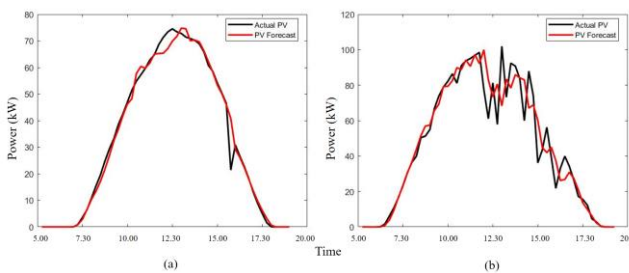


Figure 9. Forecasting result simulated with proposed parameter's value (a) winter season (b) summer season

## 5. CONCLUSION

This study proposes a new PV power forecasting model applied from statistical forecasting method called Holt-Winters forecasting using historical PV-profile data and forecasting parameter ( $\alpha$ ). The 15-minute ahead PV power forecasting is focused in this research. The simulation shows promising result without installing any additional devices to perform the forecasting. The set of suitable values for both parameters used for all season is proposed. The main advantages of the proposed method are its simplicity. Additional data, i.e. sky camera, satellite or weather condition, could improve the accuracy of the proposed technique.

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