# Forecasting of Monthly Electricity Generating for Solar PV Power Plant by Using NeuroLab Based Python: A Case Study of Thailand

Pornchai Chaweewat*, Weerakorn Ongsakul, and Kasem Pinthong

***Abstract*****—** *This paper develops forecasting tool by using Python language based artificial intelligent. The methodology starts with physical and statistic data collecting. The physical data includes solar photovoltaic (PV) power plant's capacity and location. The minimum installed capacity of a solar PV power plant is 1 MW. The statistical data includes monthly solar PV power plant's electricity generation, daily and monthly maximum, minimum and average values of local temperature, solar irradiance, and rainfall. The historical weather data are collected from NREL System Advisor Model (SAM), Thai meteorology station and local meteorology on solar PV power plant. The collecting data are fed to train an Artificial Neural Network (ANN) model. The results of ANN model are compared to the actual values. The contributions of this study are a comparison of historical weather data sources.*

***Keywords*****— Artificial neural network, solar PV forecasting, Python, NeuroLab library, Neural Network toolbox, MATLAB.**

## 1. [1] INTRODUCTION

Trend of solar photovoltaic (PV) power plant installation has been increasingly due to evidences on reducing greenhouse gas (GHG) emission on electricity generation by using renewable energy source (RES) instead of fossil fuels. Integration of RES comes with great challenging in uncertainty in resources such as solar irradiation and wind flow. Thus, a number of researches on RES focus on forecasting.

The forecast horizon where most research has been done in the day-ahead. The reason for this behavior is that most of the energy is traded in day-ahead markets, when planning and unit commitment takes place. As energy markets evolve, such as the case of energy imbalance market (EIM), intra-hour trading will become more important and thus, more research will focus on that time horizon and with a higher applicability in electricity markets. Traditionally, most a solar power forecasts were deterministic that is, for each forecast horizon they provided a single value. Nevertheless, state-of-the art papers are introducing probabilistic forecasts, which enable a better risk assessment and decision making. Compared to load or wind power forecasting, the state of probabilistic solar power forecasting is still immature and several challenges are yet to be solved [1]

In short term horizontal time, the impact of solar power forecasting improvements on solar power curtailment as well as on electricity generation, ramping, and starts and shutdowns of fossil fueled electricity generators resulted in impacts on operational electricity generation cost (summation of fuel costs, VO&M costs, and start and shutdown costs). Fig. above shows the economic value of uniform solar power forecasting improvement for different annual operational electricity generation cost. Moreover, the addition value of solar power forecasting improvement decreased for additional uniform improvements. For example, with a 13.5% solar power penetration, uniformly improving DA state-of-the-art solar power forecasting by 50% reduced annual operational electricity generation costs by $13.22 M, while the additional value of improving solar power forecasting to 100% was only $6.34 M [2].

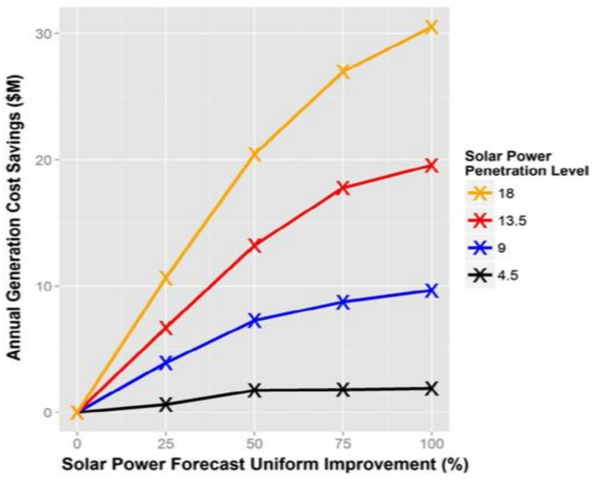


**Fig. 1. Improvement in solar power forecasting and annual generation saving cost [2].**

It is identified that, solar irradiance, temperature, wind speed and direction, humidity, cloud cover and aerosol index are major parameters to change of PV output power. It is also concluded that, solar irradiance is highly correlated with solar PV output power and follows the similar pattern. Therefore, the forecast accuracy of prediction models can be enhanced by optimizing and better selection of these correlated variables. Moreover, it is concluded that, endogenous stochastic methods such

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as autoregressive (AR), moving average (MA), autoregressive moving average (ARMA) and/or autoregressive integrated moving average (ARIMA) can be used where less number of meteorological parameters are available as model input. In addition, different classification and clustering methods can be applied for improved training the forecasting model to enhance the forecast model performance. Intelligent Learning techniques such as artificial neural network (ANN) and fuzzy logic can have applied in dynamic environment to forecast the PV output, of adequate historical patterns are available to train the network [3].

In long term solar PV generating forecasting, the grid operator can perform a better operation and long-term planning. The grid operator will also be able to perform reliable and safe maintenance planning and avoid any risks due to imbalance in power supply [4].

NREL provides access to TMY2 and TMY3 data sets and also uses these data sets in its online solar energy calculator PVWatts. There is only one TMY2 station in Thailand where locates in Bangkok as shown in Fig. 2.

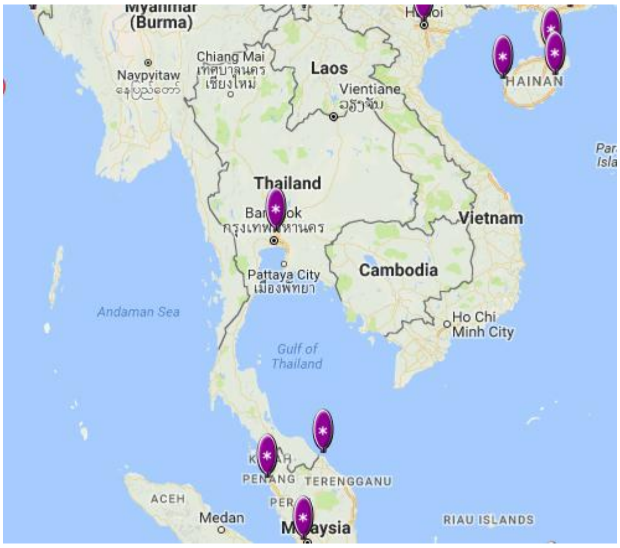



**Fig. 2. TMY2 stations locate in Thailand and nearby countries (source: PVwatt).**

In summary, monthly solar PV generating forecasting provides several benefits as below;

- Accuracy solar PV generating forecasting can help the operator to plan safe maintenance and minimize risk on power balance. Moreover, solar PV owner can ensure their revenue and financial analysis.
- Underestimate solar PV generating can cause system's stability and reliability.
- Overestimate solar PV generating can cause financial damage to solar PV owners.

Research question:

- Since PVwatt accesses to only one meteorological station in Thailand, is it provide better to forecast data on monthly solar PV production than using local meteorological weather data from Thai Department of Meteorological?
- Is NeuroLab library based Python language can perform better than neural network toolbox in MATLAB in term of time of calculation and error of forecasting?

The contributions of this paper are listed below

- To forecast monthly output of solar PV power plant in Thailand using historical local weather data collected from Thai Department of Meteorological.
- To modify algorithm to forecast solar PV generating by using NeuroLab library based on Python language.

The rest of this paper is organized as follows. The methods of data collection, construction of feed-forward neural network, learning algorithm and forecasting evaluation is described in Section 2. Section 3 discusses numerical results and discussion of this paper. The conclusion and future work will be presented in Section 4. The collected data of historical weather parameters and solar PV output will be shown in Appendices.

## 2. PROBLEM FORMULATION

Fig. 3 represents overall methodology of this study. The data collecting from both PEA and Thai Meteorological Department starts at the beginning. The installation capacity and production of solar PV are fed to compute capacity factor as target of forecasting model in training period. Location and other measure meteorological data are fed into forecasting models as input. The result from forecasting model based NeuroLab, NN toolbox and PVwatt are compared using MAE, MAPE, cumulative probability of error and computational time. The discussion and conclusion are at the end of this study.

### *2.1 Data description*

This section descripts the collected historical data and predictor data. The data is collected in 2016. The solar PV generation historical data are collected from Provincial Electricity Authority of Thailand. The historical solar PV generation data consists of location of plant, installation capacity (kW) and monthly solar PV generation (kWhr). The historical weather data is collected from Meteorological Department of Thailand. The historical weather data consists of location of measured station and monthly measured data which are cloud index, humidity, haze, fog, rain fall, minimum temperature, and maximum temperature. The average historical monthly solar PV generation and weather data are considered as input data to train forecasting model as shown in Table 1.

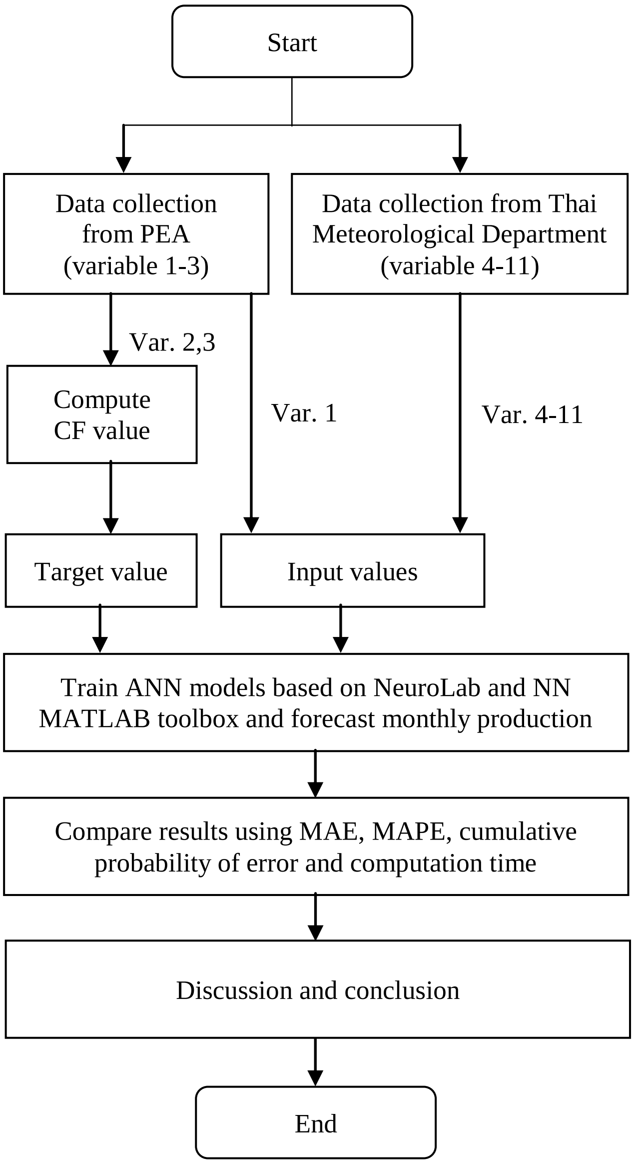



**Fig. 3. Conceptual methodology**

**Fig. 4. 4.2 kW solar PV grid-connected in AIT**

The test data is collected from solar PV power plant in Energy building, Asian Institute of Technology and meteorological measured station in Pathumthani province where the site is located. The test data is collected during January to October 2017. The till angle is 15 degrees.

**Table 1. Data description and number of collected data**

| No. of variable | Variable name | No. of collected data |
|---|---|---|
| 1 | Location of plant | 232 |
| 2 | Size of plant | 232 |
| 3 | Monthly solar PV generation | 2,784 |
| 4 | Location of meteorological station | 117 |
| 5 | Monthly cloud index | 1,317 |
| 6 | Monthly humidity | 1,371 |
| 7 | Monthly haze | 1,344 |
| 8 | Monthly fog | 1,344 |
| 9 | Monthly rainfall | 1,153 |
| 10 | Monthly minimum temperature | 1,393 |
| 11 | Monthly maximum temperature | 1,404 |

### *2.2 Capacity factor of solar PV generation*

The capacity factor (*CF*) of each solar PV generating represents the performance of power plant. In this paper, the CF is the total AC kWhr of electricity generated by the system in a month divided by the system's rated capacity in DC kW divided by number of day in the month. The values of CF for each month are calculate by equation (1):

$$CF_{i,m} = \frac{AC_{i,m}}{DC_{i,m} \times number\ of\ day_m} \tag{1}$$

where $i$ represent power plant $i$; AC is total electricity produced in month m; DC is overall installed capacity of the power plant; and number of day is number of day in the month.

### *2.3 Feed-forward neural network (FNN)*

This section descripts basic structure of FNN which consists of three layers. They are input layer, hidden layer and output layer. In multi-layer FNN, neurons are allocated in distinct layered topology as shown in Fig.3. A FNN only allows data flow in a forward direction, i.e., the data flows from the input layer neurons, through the hidden layers' neurons, and finally reaching the output layer neurons. The widely used learning method in FNN is the backpropagation algorithm. Backpropagation is a form of supervised learning in which the network is provided with examples of inputs and a target output. The training starts with random weights and biases value. The objective is to adjust them to make sure that the error is minimal. The values of the hidden layer neurons can be expressed in (2).

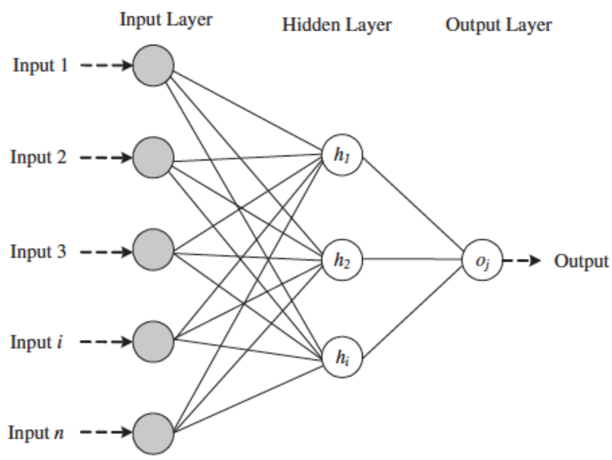



**Fig. 5. A simple three-layer feed-forward neural network [5]**

$$h_j = f_1\left(\sum_{i=1}^{n} v_{ij} x_i + \theta_j\right) \tag{2}$$

where $h_j$ is the values of the hidden layer neuron: $f_1(\cdot)$ is tangent sigmoind transfer function; xi is the value of the input and hidden layers and $\theta_j$ is the bias of the hidden layer neuron.

The hidden layer will be considered as input to the output layer and the values of the output layer neurons is shown in (3).

$$o_j = f_2\left(\sum_{i=1}^{n} w_{ij} h_i + \gamma_j\right) \tag{3}$$

where $o_j$ is the values of the hidden layer neuron; $f_2(\cdot$is a linear transfer function; $w_{ij}$ is the adjustable weight between the hidden and output layers and $\gamma_j$ is the bias of the output layer neuron.

### *2.4 Levenberg-Marguardt algorithm (LMA)*

This section illustrates how LMA can be used in FNN. Letting $e_k = R_k - Z_k,\ k = 1,\dots,N$, cost function would be defined to quantify the difference between $R_k$ and $Z_k$ in *j-th* epoch as:

$$E_j = E_j(e_k, k = 1,\dots,N) = \frac{1}{2}\sum_{k=1}^{N} e_k^2 \tag{4}$$

where $R = [R_1 \dots R_N]^T$ is a $N \times 1$ vector as the target output, $Z = [Z_1 \dots Z_N]^T$ is a $N \times 1$ vector as the ANN output, $e = [e_1 \dots e_N]^T$ is a $N \times 1$ error vector, and $N$ is the number of samples. All parameters of antecedent can be defined in a matrix as:

$$W = [c_1\ s_1 \dots c_{2n}\ s_{2n}]^T = [W_1 \dots W_{4n}]^T \tag{5}$$

where $c_1$ and $s_1$ indicate the center and standard deviation of first membership function, and so on. As mentioned before, all member ship functions have been selected as Gaussian functions.

LMA uses Jacobian matrix $J_j$ which is a gradient matrix representing the partial derivatives of $e_j$ with respect of $W_j$ [6].

$$J_j = \frac{\partial e(W_j)}{\partial (W_j)} = \frac{\partial \begin{bmatrix} e_1 \\ \vdots \\ e_N \end{bmatrix}}{\partial \begin{bmatrix} W_1 \\ \vdots \\ W_N \end{bmatrix}_j} = \begin{bmatrix} \frac{\partial e_1}{\partial W_1} & \cdots & \frac{\partial e_1}{\partial W_{4n}} \\ \vdots & \ddots & \vdots \\ \frac{\partial e_N}{\partial W_1} & \cdots & \frac{\partial e_N}{\partial W_{4n}} \end{bmatrix}_j \tag{6}$$

The LMA update for the weights is expressed as

$$W_{j+1} = W_j - ((J_j^T J_j) + \mu I)^{-1} J_j^T e(W_j) \tag{7}$$

where the factor $\mu$ adjusts its value according to the rule depicted in the LMA flowchart in Fig. 3. The flowchart shows how the LMA formula adjusts $\mu$ to cleverly switch between the coarser delta rule update finer Gauss-Newton algorithm update. In this way, the parameters of antecedent which are $c_1$, $s_1$, $c_2$, $s_2$, ... are identified by LMA [7].

### *2.5 Mean absolute error (MAE) and mean absolute percentage error (MAPE)*

This section describes evaluation of developed algorithm using MAE and MAPE. The MAE defines as the difference between the actual and forecasted monthly solar PV generation which is computed by (8). The MAPE expresses the scaled difference between the actual and forecasted monthly solar PV generation as a percentage of the actual solar PV generation. MAPE is scale independent and it can be used to compare forecast performance across different data sets. MAPE can be calculated by (9)

$$MAP = \frac{1}{N}\sum_{i=1}^{N} \left| P_a - P_f \right| \tag{8}$$

$$MAPE[\%] = \frac{100}{N}\sum_{i=1}^{N} \left| \frac{P_a - P_f}{P_a} \right| \tag{9}$$

where $P_a$ and $P_f$ are the actual and forecasted solar PV generation. $N$ is the data size.

## 3. NUMBERICAL RESULTS AND DISCUSSION

This chapter presents simulation results and evaluation of trained model using collected local weather data from Thai Meteorological Department. The training period starts from January to December 2016. The testing period is during January to October 2017. The solar PV generating data collected from PVwatt at tested site is used as benchmark.

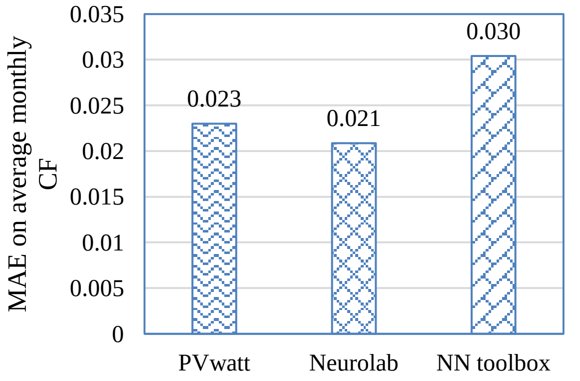



**Fig. 6. MAE values on average monthly CF forecasting for PVwatt, NeuroLab and NN toolbox.**

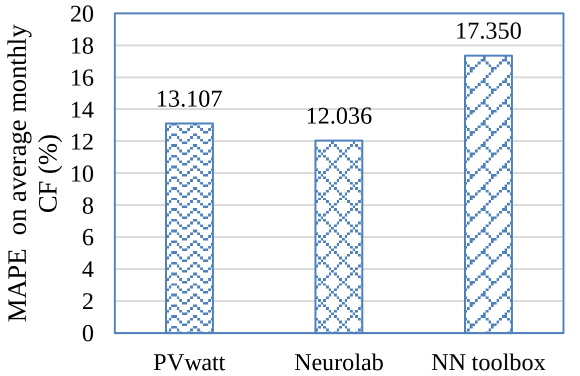
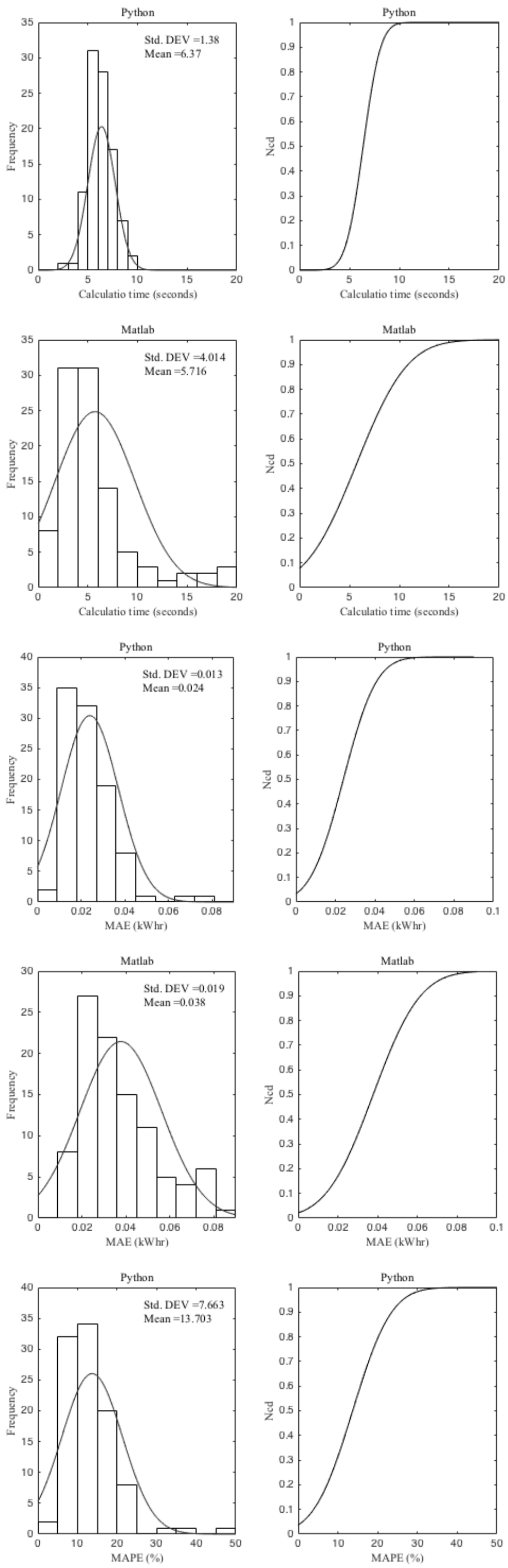



**Fig. 7. MAPE values on average monthly CF forecasting for PVwatt, NeuroLab and NN toolbox**

According to average monthly capacity factor forecasting, MAE and MAPE results in Fig. 3 and 4, three are difference in results of PVwatts and proposed methods. NeuroLab drops down these MAE on for 0.002 and 0.009 comparing to PVwatts and NN toolbox Then, MAPE of NeuroLab is found lower than PVwatt and NN toolbox. Thus, the proposed NeuroLab based forecasting model perform the excellence results in AIT solar PV site.

The histograms, normalized distributed lines and cumulative normalize distributed lines plots of NeuroLab and Neural Network toolbox (NN) are shown in Fig. 5. The comparison between NeuroLab's and NN toolbox's results show that NeuroLab consume more calculating time but less standard deviation of calculating time. However, NeuroLab perform better in forecasting accuracy. The average monthly MAE is less than NN toolbox by 0.014 kWhr. Moreover, NeuroLab provide lower MAPE by 7.78%.



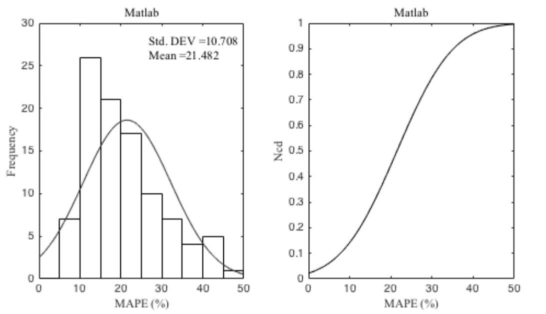



**Fig. 8. Distribution histogram and cumulative distribution probability of calculating time, MAE and MRE for NeuroLab and NN toolbox.**

## 4. CONCLUSION

This paper presents a modified neural network library and toolbox which are NeuroLab based python and neural network toolbox base MATLAB as monthly solar PV generation forecasting using local weather data from the Thai Meteorological Department. The result of MAE shows the significant performance of using historical weather data better than PVwatt which using TMYs data. Moreover, NeuroLab library based python shows excellent performance comparing to neural network toolbox based MATLAB.

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## Appendix

**Table A-1. Historical monthly solar PV generating distributed by area and size for training the purposed model.**

| Area* | Size** | No. of site | Average monthly capacity factor | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | Jan | Feb | Mar | Apr | May | Jun | Jul | Aug | Sep | Oct | Nov | Dec |
| 1 | small | 18 | 0.144 | 0.173 | 0.167 | 0.178 | 0.160 | 0.147 | 0.146 | 0.151 | 0.150 | 0.139 | 0.160 | 0.145 |
| | medium | 7 | 0.187 | 0.205 | 0.199 | 0.215 | 0.195 | 0.172 | 0.177 | 0.179 | 0.171 | 0.177 | 0.197 | 0.183 |
| | large | 11 | 0.218 | 0.238 | 0.232 | 0.246 | 0.228 | 0.203 | 0.209 | 0.214 | 0.207 | 0.209 | 0.233 | 0.218 |
| 2 | small | 2 | 0.147 | 0.170 | 0.150 | 0.150 | 0.142 | 0.147 | 0.144 | 0.161 | 0.148 | 0.136 | 0.159 | 0.142 |
| | medium | 8 | 0.175 | 0.204 | 0.202 | 0.209 | 0.180 | 0.166 | 0.162 | 0.183 | 0.168 | 0.165 | 0.195 | 0.176 |
| | large | 1 | 0.157 | 0.176 | 0.166 | 0.184 | 0.155 | 0.149 | 0.150 | 0.125 | 0.093 | 0.091 | 0.169 | 0.165 |
| 3 | small | 1 | 0.249 | 0.247 | 0.248 | 0.275 | 0.221 | 0.221 | 0.211 | 0.207 | 0.210 | 0.203 | 0.224 | 0.223 |
| | medium | 5 | 0.216 | 0.218 | 0.220 | 0.241 | 0.228 | 0.198 | 0.202 | 0.207 | 0.199 | 0.200 | 0.205 | 0.199 |
| | large | 18 | 0.201 | 0.209 | 0.208 | 0.228 | 0.213 | 0.191 | 0.191 | 0.193 | 0.188 | 0.190 | 0.197 | 0.189 |

| | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 4 | small | 5 | 0.171 | 0.179 | 0.172 | 0.173 | 0.163 | 0.136 | 0.133 | 0.125 | 0.140 | 0.157 | 0.152 | 0.153 |
| | medium | 9 | 0.178 | 0.190 | 0.184 | 0.184 | 0.184 | 0.151 | 0.148 | 0.134 | 0.148 | 0.170 | 0.171 | 0.170 |
| | large | 1 | 0.208 | 0.215 | 0.205 | 0.209 | 0.209 | 0.201 | 0.183 | 0.188 | 0.195 | 0.200 | 0.197 | 0.210 |
| 5 | small | 0 | None | None | None | None | None | None | None | None | None | None | None | None |
| | medium | 1 | 0.183 | 0.143 | 0.198 | 0.218 | 0.199 | 0.180 | 0.176 | 0.177 | 0.174 | 0.203 | 0.209 | 0.200 |
| | large | 7 | 0.212 | 0.229 | 0.227 | 0.240 | 0.222 | 0.190 | 0.189 | 0.180 | 0.189 | 0.219 | 0.216 | 0.210 |
| 6 | small | 2 | 0.116 | 0.135 | 0.136 | 0.148 | 0.150 | 0.136 | 0.136 | 0.128 | 0.120 | 0.129 | 0.137 | 0.131 |
| | medium | 18 | 0.178 | 0.205 | 0.196 | 0.211 | 0.201 | 0.180 | 0.185 | 0.183 | 0.176 | 0.179 | 0.200 | 0.188 |
| | large | 7 | 0.183 | 0.208 | 0.197 | 0.210 | 0.199 | 0.175 | 0.181 | 0.183 | 0.172 | 0.187 | 0.201 | 0.195 |
| 7 | small | 1 | 0.114 | 0.148 | 0.127 | 0.133 | 0.138 | 0.132 | 0.123 | 0.118 | 0.112 | 0.126 | 0.130 | 0.126 |
| | medium | 21 | 0.138 | 0.176 | 0.155 | 0.159 | 0.161 | 0.152 | 0.147 | 0.145 | 0.142 | 0.157 | 0.168 | 0.163 |
| | large | 19 | 0.196 | 0.248 | 0.222 | 0.219 | 0.215 | 0.199 | 0.195 | 0.193 | 0.185 | 0.209 | 0.224 | 0.221 |
| 8 | small | 1 | 0.198 | 0.264 | 0.230 | 0.243 | 0.235 | 0.214 | 0.171 | 0.221 | 0.203 | 0.234 | 0.242 | 0.233 |
| | medium | 9 | 0.180 | 0.222 | 0.188 | 0.191 | 0.193 | 0.180 | 0.176 | 0.174 | 0.162 | 0.194 | 0.202 | 0.193 |
| | large | 6 | 0.192 | 0.250 | 0.222 | 0.223 | 0.203 | 0.207 | 0.216 | 0.201 | 0.183 | 0.206 | 0.210 | 0.202 |
| 9 | small | 1 | 0.082 | 0.096 | 0.075 | 0.067 | 0.072 | 0.098 | 0.100 | 0.083 | 0.073 | 0.069 | 0.077 | 0.067 |
| | medium | 16 | 0.185 | 0.224 | 0.212 | 0.222 | 0.205 | 0.195 | 0.197 | 0.201 | 0.179 | 0.195 | 0.206 | 0.198 |
| | large | 20 | 0.213 | 0.255 | 0.240 | 0.243 | 0.223 | 0.213 | 0.219 | 0.220 | 0.199 | 0.220 | 0.228 | 0.223 |
| 10 | small | 6 | 0.176 | 0.191 | 0.190 | 0.196 | 0.171 | 0.142 | 0.137 | 0.132 | 0.131 | 0.121 | 0.139 | 0.142 |
| | medium | 4 | 0.200 | 0.201 | 0.202 | 0.214 | 0.190 | 0.168 | 0.166 | 0.164 | 0.156 | 0.148 | 0.171 | 0.165 |
| | large | 0 | None | None | None | None | None | None | None | None | None | None | None | None |
| 11 | small | 2 | 0.066 | 0.051 | 0.038 | 0.055 | 0.064 | 0.070 | 0.049 | 0.046 | 0.049 | 0.043 | 0.046 | 0.034 |
| | medium | 0 | None | None | None | None | None | None | None | None | None | None | None | None |
| | large | 0 | None | None | None | None | None | None | None | None | None | None | None | None |
| 12 | small | 3 | 0.086 | 0.103 | 0.109 | 0.092 | 0.071 | 0.069 | 0.079 | 0.083 | 0.088 | 0.084 | 0.080 | 0.071 |
| | medium | 0 | None | None | None | None | None | None | None | None | None | None | None | None |
| | large | 0 | None | None | None | None | None | None | None | None | None | None | None | None |

*Area

** Size of plant: small (less than 1 MW), medium (1-5 MW), large (above 5 MW)

**Table A-2. Actual monthly solar PV generation at AIT and forecasted data from PVwatt[8] during January to October, 2017**

| Month | Number of days in month | Monthly solar PV generation (kWhr) | |
|---|---|---|---|
| | | AIT | PVwatt [8] |
| January | 31 | 508.66 | 505 |
| February | 29 | 544.07 | 486 |
| March | 31 | 522.94 | 576 |
| April | 30 | 574.76 | 513 |
| May | 31 | 502.9 | 470 |
| June | 30 | 559.16 | 458 |
| July | 31 | 537.28 | 484 |
| August | 31 | 554.77 | 416 |
| September | 30 | 550.55 | 438 |
| October | 31 | 549.12 | 446 |

**Table A-3. Actual monthly capacity factor at AIT and calculaed capacity from PVwatt[8] during January to October, 2017**

| Month | Number of days in month | Capacity factor | |
|---|---|---|---|
| | | AIT | PVwatt [8] |
| January | 31 | 0.1628 | 0.1616 |
| February | 29 | 0.1741 | 0.1555 |
| March | 31 | 0.1674 | 0.1843 |
| April | 30 | 0.1839 | 0.1642 |
| May | 31 | 0.1609 | 0.1504 |
| June | 30 | 0.1789 | 0.1466 |
| July | 31 | 0.1719 | 0.1549 |
| August | 31 | 0.1775 | 0.1331 |
| September | 30 | 0.1762 | 0.1402 |
| October | 31 | 0.1757 | 0.1427 |
| MAE | | | 0.0229 |
| MAPE (%) | | | 13.107 |

**Table A-4. Results of calculation time, MAE and MAPE on average monthly capacity factor using NeuroLab based Python and NN toolbox based MATLAB**

| Sample | NeuroLab | | | NN toolbox | | |
|---|---|---|---|---|---|---|
| | Time | MAE | MAPE | Time | MAE | MAPE |
| 1 | 10.209 | 0.038 | 22.052 | 12.947 | 0.052 | 29.950 |
| 2 | 7.935 | 0.016 | 9.001 | 3.378 | 0.030 | 16.993 |
| 3 | 5.998 | 0.015 | 8.270 | 2.895 | 0.044 | 24.535 |
| 4 | 5.585 | 0.012 | 6.311 | 4.056 | 0.018 | 10.021 |
| 5 | 4.740 | 0.018 | 10.068 | 3.516 | 0.017 | 9.389 |
| 6 | 5.647 | 0.015 | 8.994 | 11.273 | 0.070 | 39.041 |
| 7 | 7.355 | 0.012 | 7.374 | 5.422 | 0.066 | 37.331 |
| 8 | 5.000 | 0.037 | 20.818 | 4.804 | 0.074 | 42.202 |
| 9 | 4.381 | 0.018 | 10.616 | 3.262 | 0.032 | 18.069 |
| 10 | 6.968 | 0.075 | 45.446 | 7.378 | 0.019 | 10.855 |
| 11 | 5.138 | 0.015 | 8.401 | 7.236 | 0.056 | 31.752 |
| 12 | 4.868 | 0.032 | 17.896 | 4.840 | 0.040 | 22.424 |
| 13 | 5.239 | 0.022 | 12.428 | 4.209 | 0.080 | 45.443 |
| 14 | 7.664 | 0.018 | 10.471 | 4.009 | 0.022 | 12.979 |
| 15 | 5.677 | 0.013 | 7.269 | 1.592 | 0.029 | 16.402 |
| 16 | 6.005 | 0.019 | 10.802 | 2.982 | 0.040 | 23.599 |
| 17 | 6.012 | 0.015 | 8.986 | 3.907 | 0.020 | 11.251 |
| 18 | 5.999 | 0.018 | 10.221 | 1.721 | 0.056 | 31.462 |
| 19 | 5.319 | 0.030 | 15.997 | 6.536 | 0.028 | 15.901 |
| 20 | 5.644 | 0.025 | 14.951 | 3.527 | 0.045 | 24.947 |
| 21 | 5.351 | 0.023 | 13.043 | 9.070 | 0.039 | 22.437 |
| 22 | 6.568 | 0.028 | 15.649 | 4.372 | 0.038 | 21.316 |
| 23 | 5.997 | 0.024 | 13.957 | 3.994 | 0.039 | 22.240 |
| 24 | 7.368 | 0.030 | 17.421 | 2.155 | 0.073 | 43.448 |
| 25 | 6.688 | 0.021 | 11.956 | 4.445 | 0.029 | 16.113 |
| 26 | 5.918 | 0.040 | 22.311 | 4.503 | 0.030 | 17.063 |
| 27 | 7.001 | 0.009 | 4.864 | 5.525 | 0.015 | 8.610 |

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|---|---|---|---|---|---|---|
| 28 | 4.499 | 0.033 | 19.066 | 4.037 | 0.054 | 30.980 |
| 29 | 6.940 | 0.015 | 8.960 | 5.501 | 0.026 | 15.425 |
| 30 | 10.993 | 0.038 | 20.913 | 7.439 | 0.023 | 13.020 |
| 31 | 6.407 | 0.013 | 7.388 | 2.846 | 0.029 | 16.053 |
| 32 | 6.473 | 0.024 | 13.214 | 10.795 | 0.031 | 17.553 |
| 33 | 6.117 | 0.022 | 12.662 | 2.831 | 0.026 | 14.709 |
| 34 | 8.724 | 0.033 | 18.597 | 1.295 | 0.038 | 21.798 |
| 35 | 7.239 | 0.019 | 10.397 | 17.785 | 0.029 | 17.003 |
| 36 | 6.782 | 0.031 | 17.758 | 1.981 | 0.028 | 15.582 |
| 37 | 6.477 | 0.028 | 15.594 | 8.132 | 0.036 | 20.621 |
| 38 | 5.904 | 0.014 | 8.103 | 19.329 | 0.024 | 13.001 |
| 39 | 7.744 | 0.011 | 6.601 | 15.378 | 0.052 | 30.008 |
| 40 | 4.994 | 0.017 | 9.952 | 5.359 | 0.035 | 20.395 |
| 41 | 9.562 | 0.020 | 11.295 | 4.723 | 0.021 | 11.606 |
| 42 | 5.027 | 0.011 | 6.091 | 5.637 | 0.088 | 51.924 |
| 43 | 5.011 | 0.029 | 16.287 | 2.749 | 0.029 | 16.224 |
| 44 | 6.381 | 0.028 | 15.850 | 5.476 | 0.060 | 34.383 |
| 45 | 6.185 | 0.015 | 8.798 | 5.806 | 0.037 | 20.652 |
| 46 | 6.173 | 0.053 | 31.918 | 3.232 | 0.024 | 13.408 |
| 47 | 7.495 | 0.065 | 36.682 | 4.752 | 0.048 | 27.320 |
| 48 | 5.415 | 0.011 | 6.045 | 3.247 | 0.021 | 12.031 |
| 49 | 5.552 | 0.016 | 8.870 | 2.212 | 0.029 | 16.469 |
| 50 | 6.930 | 0.023 | 12.683 | 3.563 | 0.020 | 11.574 |
| 51 | 3.990 | 0.018 | 10.389 | 1.008 | 0.024 | 13.565 |
| 52 | 5.930 | 0.014 | 7.822 | 9.158 | 0.030 | 17.560 |
| 53 | 6.200 | 0.019 | 10.661 | 3.616 | 0.048 | 27.120 |
| 54 | 6.408 | 0.017 | 9.755 | 4.454 | 0.068 | 39.003 |
| 55 | 7.084 | 0.022 | 12.645 | 6.716 | 0.075 | 44.140 |
| 56 | 4.697 | 0.013 | 7.978 | 4.169 | 0.045 | 26.018 |
| 57 | 6.083 | 0.022 | 12.465 | 15.742 | 0.025 | 14.000 |
| 58 | 5.068 | 0.017 | 9.743 | 5.664 | 0.017 | 9.960 |
| 59 | 5.436 | 0.016 | 9.198 | 1.547 | 0.038 | 21.969 |
| 60 | 4.847 | 0.007 | 3.979 | 3.877 | 0.018 | 9.914 |
| 61 | 5.999 | 0.035 | 19.936 | 3.275 | 0.025 | 14.131 |
| 62 | 8.072 | 0.021 | 11.539 | 7.015 | 0.024 | 13.286 |
| 63 | 6.323 | 0.024 | 13.777 | 2.807 | 0.017 | 9.368 |
| 64 | 7.450 | 0.039 | 21.864 | 6.935 | 0.047 | 25.668 |
| 65 | 5.944 | 0.034 | 19.344 | 6.525 | 0.115 | 64.653 |
| 66 | 9.644 | 0.034 | 19.095 | 7.767 | 0.052 | 30.177 |

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|---|---|---|---|---|---|---|
| 67 | 4.689 | 0.020 | 11.711 | 2.600 | 0.044 | 24.587 |
| 68 | 6.570 | 0.025 | 14.435 | 9.247 | 0.048 | 27.421 |
| 69 | 7.027 | 0.018 | 10.062 | 18.055 | 0.072 | 42.115 |
| 70 | 8.380 | 0.019 | 10.700 | 17.397 | 0.029 | 16.765 |
| 71 | 7.468 | 0.011 | 6.114 | 4.733 | 0.023 | 13.179 |
| 72 | 5.765 | 0.013 | 7.324 | 3.464 | 0.026 | 14.448 |
| 73 | 6.611 | 0.018 | 10.566 | 2.428 | 0.046 | 25.628 |
| 74 | 6.520 | 0.027 | 15.084 | 19.089 | 0.024 | 13.549 |
| 75 | 6.488 | 0.011 | 6.582 | 3.479 | 0.027 | 15.242 |
| 76 | 8.632 | 0.033 | 18.428 | 3.153 | 0.030 | 17.147 |
| 77 | 6.900 | 0.016 | 9.247 | 1.951 | 0.028 | 15.476 |
| 78 | 5.710 | 0.041 | 23.448 | 2.095 | 0.026 | 14.443 |
| 79 | 6.430 | 0.035 | 19.991 | 1.904 | 0.015 | 8.925 |
| 80 | 6.440 | 0.026 | 14.512 | 4.687 | 0.046 | 26.120 |
| 81 | 5.294 | 0.026 | 14.478 | 2.301 | 0.048 | 26.530 |
| 82 | 7.191 | 0.021 | 12.115 | 2.711 | 0.027 | 14.807 |
| 83 | 7.416 | 0.013 | 7.647 | 5.606 | 0.019 | 10.773 |
| 84 | 5.930 | 0.014 | 7.820 | 7.808 | 0.042 | 23.742 |
| 85 | 2.052 | 0.009 | 5.323 | 4.896 | 0.036 | 20.404 |
| 86 | 8.953 | 0.015 | 8.014 | 4.710 | 0.029 | 16.145 |
| 87 | 6.437 | 0.029 | 16.431 | 11.206 | 0.023 | 13.522 |
| 88 | 5.861 | 0.025 | 14.320 | 8.016 | 0.056 | 31.377 |
| 89 | 6.806 | 0.028 | 16.265 | 3.658 | 0.036 | 20.102 |
| 90 | 5.541 | 0.020 | 11.144 | 4.815 | 0.021 | 12.133 |
| 91 | 7.682 | 0.030 | 16.654 | 2.513 | 0.029 | 16.380 |
| 92 | 4.172 | 0.026 | 14.499 | 7.254 | 0.020 | 11.286 |
| 93 | 5.126 | 0.022 | 12.367 | 5.422 | 0.025 | 13.873 |
| 94 | 5.822 | 0.033 | 18.819 | 5.820 | 0.034 | 19.097 |
| 95 | 5.468 | 0.039 | 22.164 | 6.496 | 0.044 | 24.796 |
| 96 | 7.001 | 0.022 | 12.289 | 3.595 | 0.049 | 27.556 |
| 97 | 8.309 | 0.093 | 54.420 | 7.369 | 0.017 | 9.766 |
| 98 | 4.655 | 0.015 | 8.158 | 4.474 | 0.065 | 37.712 |
| 99 | 7.506 | 0.016 | 9.238 | 6.495 | 0.074 | 41.913 |
| 100 | 8.065 | 0.036 | 20.426 | 4.232 | 0.024 | 13.243 |
| Mean | 6.192 | 0.021 | 12.036 | 4.595 | 0.030 | 17.350 |
| Std. DEV | 1.369 | 0.013 | 7.625 | 3.994 | 0.019 | 10.655 |
| Max | 10.993 | 0.093 | 54.420 | 19.329 | 0.115 | 64.653 |
| Min | 2.052 | 0.007 | 3.979 | 1.008 | 0.015 | 8.610 |