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Solar Irradiance Forecasting Model for Pulau Pinang using Artificial Neural Network

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Abstract

One of the important parameters for solar photovoltaic (PV) optimization is solar irradiance. Solar irradiance can be defined as the rate of solar energy when it falls onto the surface. Solar irradiance can make an importance decision, efficiency, performance, and maintenance on energy yield in the future. However, solar irradiance has high degree of uncertainty due to environmental and meteorological condition such as cloud cover, haze, fog and rapid change in ambient temperature. Thus, by forecasting solar irradiance, it would improve the efficiency, performance, and operation of the PV system in order to generate a maximum power. This research aims to develop a forecasting model of solar irradiance based on meteorological data from year 2018 in Pulau Pinang. The forecasting model is developed based on Artificial Neural Network (ANN) Multilayer Perceptron (MLP) method. The accuracy of the forecasting model is compared with the data from The National Aeronautics and Space Administration (NASA) and Sustainable Energy Development Authority (SEDA). The result shows that the forecasting model is able to deliver a good result with the correlation coefficient result of r = 0.82 (forecasted vs NASA) and r = 0.78 (forecasted vs SEDA). Thus, this solar irradiance forecasting model is able to predict almost the same value as the NASA and SEDA and can potentially be used to assist in evaluating and predicting the power output efficiency of the solar PV plant. Hence, this model can be regarded as an important tool in planning and managing the operation of PV system. others' blogs. Moreover, interview results showed that reflective journals contributed their personal and professional development.

Keywords: Solar irradiance, Artifical neural network, Forecasting model, Solar photovoltaic system, Multi-layer perceptron

I. INTRODUCTION

Pulau Pinang is located at northwest coast of Peninsular Malaysia that is situated at a coordinate of latitude 5 o 18’ and longitude 100o16’. The weather is typically hot and humid throughout the year with an annual northwest and southwest monsoon (Baharin, Abd Rahman, Hassan, & Kim, 2013). The location receives almost equal amount of sunshine daily. Research on renewable energy specifically the solar photovoltaic (PV) system has been increasing and high demand in Malaysia (Damanhuri, Othman, Ibrahim, Radzali, & Mohd, 2010). One of the importance parameter for solar PV performance is the solar irradiance (Voyant et al., 2017). However, the environment and meteorological condition may affect the solar radiation especially in tropical climate. These situations will cause an instability in photovoltaic system performance. Study shows that a good forecast result can help to reduce the impact of photovoltaic (PV) output uncertainty on the grid (do Nascimento, Braga, Campos, Naspolini, & Rüther, 2020). With such result of good forecasting, system reliability can be improved, power quality can be controlled, and penetration of PV system will be increased.

However, solar irradiance has high degree of uncertainty due to environment and meteorological condition such as cloud cover, haze, fog, rapid change in ambient temperature and irradiance. Thus it leads to an instability of PV system (Bonkaney, Madougou, & Adamou, 2017). Therefore, forecasting of solar PV can help in managing and improve the overall performance of solar PV plant (Feng et al., 2020). In order to overcome this situation, the prediction of solar irradiance is very important. Hypothetically, with this prediction, it will better improve the operation particularly in planning and managing the solar PV system.

PV module technology has become one of the most demand in energy technology. PV system is highly variable due to its dependence on meteorological condition (Creayla, Garcia, & Macabebe, 2017; Othman, Zainodin, Anuar, & Damanhuri, 2017). Predicting solar irradiance means that the output of PV is forecasted one or more step ahead of time. Hence, it will also improve the operation of various application of power system.

Several studies have been carried out using various methods to forecast the solar irradiance (Diagne, David, Lauret, Boland, & Schmutz, 2013; Kumar, Yagli, Kashyap, & Srinivasan, 2020; Lorenz et al., 2009; Madhiarasan & Deepa, 2017). Various statistical methods have been proposed for forecasting the solar irradiance including Numerical Weather Prediction (NWP) (Chow et al., 2011; Perez et al., 2010), Autoregressive Integrated Moving Average (ARIMA) (Yang, Jirutitijaroen, & Walsh, 2012) and others (Yang et al., 2013). Recently, studies have used an Artificial Neural Network (ANN) model during the forecasting process as it is regarded as less complex compared to the other conventional forecasting method.

A study uses ANN model with K- Nearest Neighbor (kNN) algorithm to forecast the solar irradiance. While the kNN-ANN manages to produce a good result, it is thought the forecasting performance might not be available as it is deeply impacted by the climate change and patterns of the cloud (Pedro & Coimbra, 2015). This kNN model is not suitable during cloudy day and it takes a longer time to react and correct its predictions. Although, the ANN method is widely used in many forecasting models, there are still rooms for improvement in order to better forecast this solar irradiance. Hence, this study proposes to implement this ANN with Multilayer Perceptron (MLP) method to forecast the solar irradiance specifically in Pulau Pinang, Malaysia. This study will aim at continuously forecasting the solar irradiance using the present value of mean daily solar irradiance from meteorological data from year 2018 in Pulau Pinang.

II. METHODOLOGY

Relationship between solar irradiance and weather variation

Solar irradiance is defined as the amount of electromagnetic energy incident on a surface per unit time and per unit area (Wang et al., 2015). Computation of the solar or shortwave component of the radiant energy budget of an organism requires estimation of flux densities for at least three radiation streams: direct irradiance on a surface perpendicular to the beam (G_p), diffuse sky irradiance on a horizontal plane (G_d), and reflected radiation from the ground (G_r) as depicted in Figure 1.

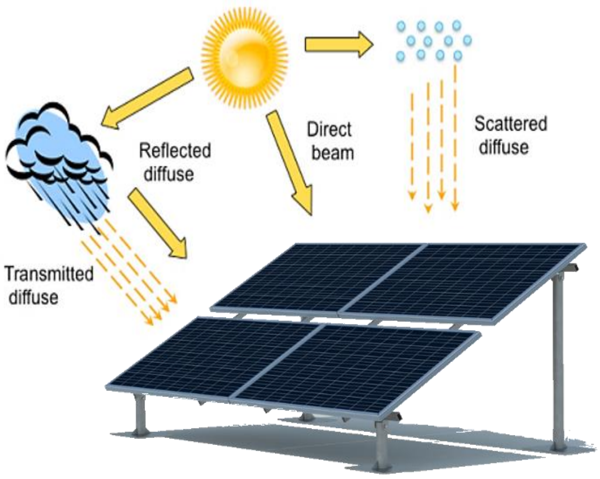

Figure 1. llustration of various radiation sources for solar irradiance

In addition to these, sometimes the beam irradiates on a horizontal surface G_b and the total (beam plus diffuse) irradiance of a horizontal surface G_t need to be known. G_t is referred to as the global irradiance.

$$G_b = G_p + cos\varphi \qquad (1)$$

$$G_t = G_s + G_d \qquad (2)$$

where φ is the solar zenith angle.

G_p is expected to be a function of the distance the solar beam travels through the atmosphere, the transmittance of the atmosphere, and the incident flux density. It can be expressed as:

$$G_p = G_{po}\tau^m \qquad (3)$$

where G_{po}, is the extraterrestrial flux density in the waveband of interest, normal to the solar beam. While τ is the atmospheric transmittance and m is the optical air mass number, or the ratio of slant path length through the atmosphere to zenith path length. For zenith angles less than 80°, refraction effects in the atmosphere are negligible, and m is given by:

$$m = \frac{\rho_a}{101.3 \cos\varphi} \qquad (4)$$

The ratio kPa/101.3 is atmospheric pressure at the observation site divided by sea level atmospheric pressure and corrects for altitude effects. The τ on the clear day is defined around 0.75 (Campbell & Norman, 2012).

The actual amount of diffuse radiation that reach to the ground is hard to configure since it depends, in part, on the albedo of the ground. For example, the sky is brighter when the ground is snow covered than it is when the ground is covered with dense, dark vegetation. By ignoring these complications, approximate values can be computed for sky diffuse radiation on clear days using an empirical equation in (5):

$$S_d = 0.3\,(1 - \tau^m)S_{po}\cos\varphi \qquad (5)$$

The airmass factor partially compensates for the effect of the cosine factor in equation (5), so that the diffuse radiation remains relatively constant throughout clear days. Note that as the dust and haze increase, beam radiation is decreased, and diffuse radiation increases.

Due to the strong correlation between some meteorological parameters and irradiance, these parameters are directly influenced by irradiance. Therefore, these parameters can reflect the changes of irradiance and can be considered as the input of the ANN forecasting model.

Artifical Neural Network (ANN)

ANN has been used widely in numerous application areas. Noticeably, ANN with Multilayer Perceptron (MLP) is commonly used model that uses a back-propagation training algorithm. A properly trained ANN will be able to achieve the accurate the estimation of any nonlinear mapping. This ANN MLP application is the most well-known ANN architecture to solve any scientific issues (Ettayyebi & El Himdi, 2018). ANNs with MLP architecture contain minimum one layer of hidden neurons and one output layer (Yang et al., 2012).

Figure 2 portrays the implemented structure of the MLP. This can be expressed by the following input and output parameter relationship as below:

$$\left(G_1(t+1), G_2(t+1)..G_{24}\,(t+1)\right) = f(G(t), P(t), t \tag{6}$$

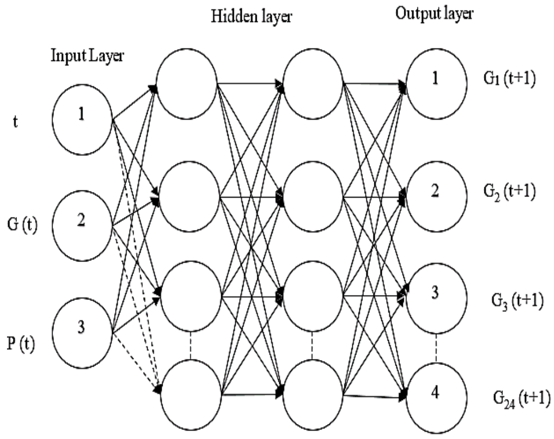

Figure 2. The MLP of ANN (Wang, Mi, Su, & Zhao, 2012)

The MLP permits to forecast 24-h ahead of solar irradiance using the actual mean value of solar irradiance, $G(t)$, air pressure, $P(t)$, and the day of the month, t. The f function is a non-linear approximation function, which can be estimated based on the weights and the bias of the optimal MLP structure.

Thus, the proposed ANN MLP is used for modelling of forecasting solar irradiance based on input and output parameter. The time scale of this forecasting method is one-day ahead. The input parameter is the air pressure in kPa while the daily solar irradiance is the output.

Figure 3 shows the flowchart of the proposed system. In this research, to forecast the solar irradiance, the MATLAB software is used. The ANN Network is done by using the nntool in this MATLAB software. Air pressure is used as the input data and the mean daily solar irradiance as the target data. Then, the data are ready to train by setting the iteration to 1000 epoch. Results obtained from the ANN MLP process will be compared with data gathered from Sustainable Energy Development Authority (SEDA) and National Aeronautics and Space Administration (NASA).

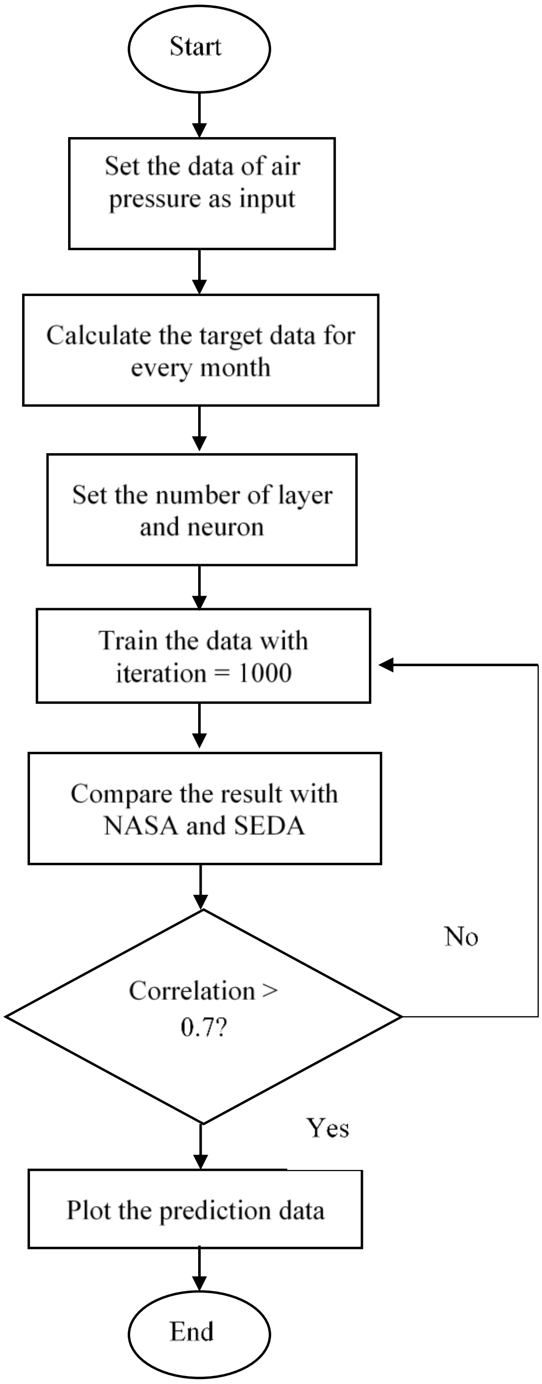

Figure 3. Flowchart of the overall system

Figure 4 shows the neural network tools for this model. There are 20 hidden layers for this model. As mentioned, the input is the air pressure and the epoch is set up to 1000 epoch to train. Then, the output result will be obtained. If the correlation result is less than 0.7, the data will be trained it again until the correlation coefficient is 0.7 and above. The samples are separated into training, validation and test sets automatically.

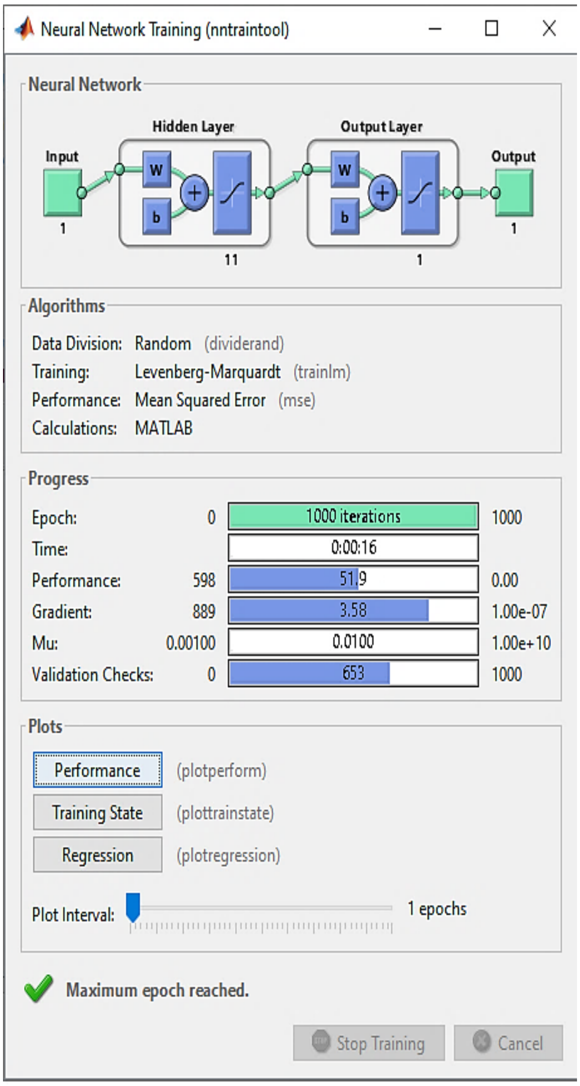

Figure 4. The Neural Network training for the developed model

Data Collection

A set of air pressure data was gathered from Penang Meteorological Office. A total of 8760 air pressure data (every hour of the year, 2018) is used as the input for the system.

Data Analysis

For this research, there are a lot of aspect that need to be considered. The information data will be collected and gathered for the process. To obtain the best solar irradiance, the error matric is used. Practically, Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) is used to evaluate the forecasting results (Madhiarasan & Deepa, 2017). These MAE and RMSE can be calculated by using the equation below:

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(G_{forecast} - G_{measured}\right)^2} \qquad (7)$$

Usually, RMSE are used as the main score to compare the forecasted irradiance, $G_{forecast}$ to measured irradiance, $G_{measured}$. N is denoted as the number of evaluated data pairs (Lorenz et al., 2009).

$$MAE = \frac{\sum_{i=1}^{N}\left(G_{forecast} - G_{measured}\right)}{N} \qquad (8)$$

III. RESULTS AND DISCUSSIONS

The solar irradiance output peak selected in any typical day occur is in between 11 a.m. until 4 p.m. The problem that had been facing by using this method is when choosing a suitable method to specify the activation function and the number of neurons in hidden layer. The most important to get the result is the selection of the hidden nodes in MLPs.

The comparison between the forecasted data and measured data had been observed. The analysis is estimated in 5 hours within a day. Figure 5 shows the total average of solar irradiance on the 1st January, 1st June and 1st November of 2018. This result is taken to observe the accuracy of the measured irradiance and the forecasted by using ANN hourly. The peak of solar irradiance output is estimated to occur around 11 am to 4 pm as the forecasted hourly average on every hour.

In term of irradiation, the result in the Figure 6 is obtained by the calculation of solar irradiance in Pulau Pinang which is almost like the SEDA and NASA data. Note that the average daily irradiance in October, November and December is very low due to the Northeast Monsoon which is more rainfall compared to the Southwest Monsoon. The highest total average solar irradiation in Pulau Pinang occur in March which is 5.77 kWh/m^2. The lowest average solar irradiation occurs during rainfall season which is in October with the value of 4.63 kWh/m^2.

Table 1 summarized the average value of solar irradiation for every month in 2018 for forecasted, NASA and SEDA. It can be seen than the average solar irradiation for that particular year was 5.04 kWh/m^2 for forecasted model, 5.08 kWh/m^2 for NASA and 4.96 kWh/m^2 for SEDA.

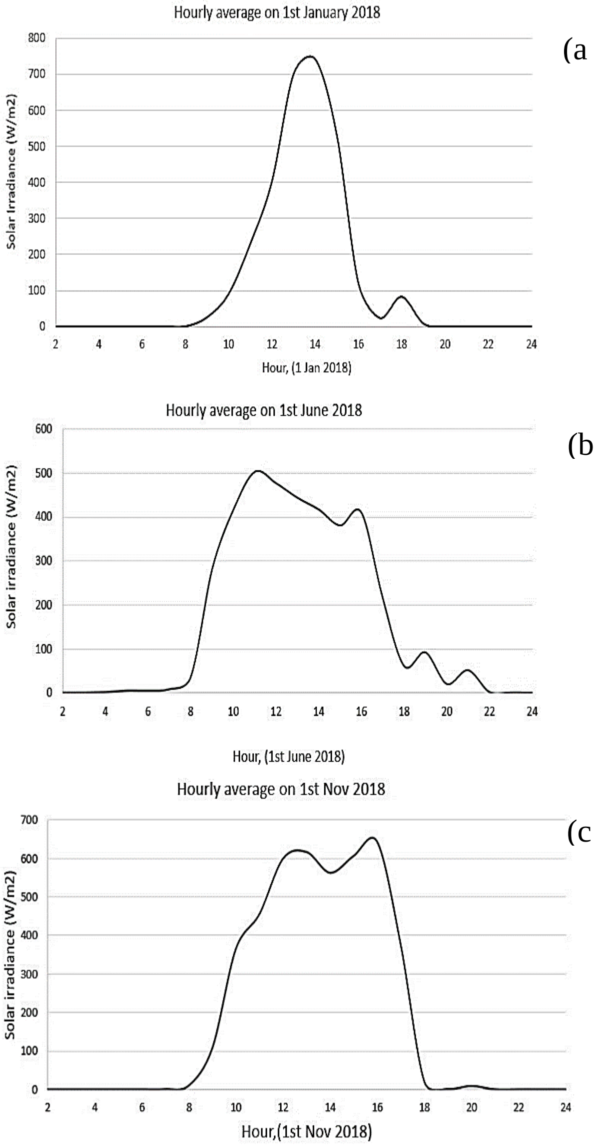

Figure 5. The average hourly of solar irradiance in Pulau Pinang; (a) January, (b) June and (c) November

Further validation is made to verify the accuracy of the forecasted performance through correlation coefficient, *r*, RMSE and MAE. The correlation coefficient gives an indication on how much the measured and forecasted data are closely related to each other. Meanwhile RMSE provides the information on short-form performance and represents a measure of variation of forecasted value around measured data. Table 2 tabulates the overall performance based on *r*, RMSE and MAE for forecasted data against NASA and SEDA.

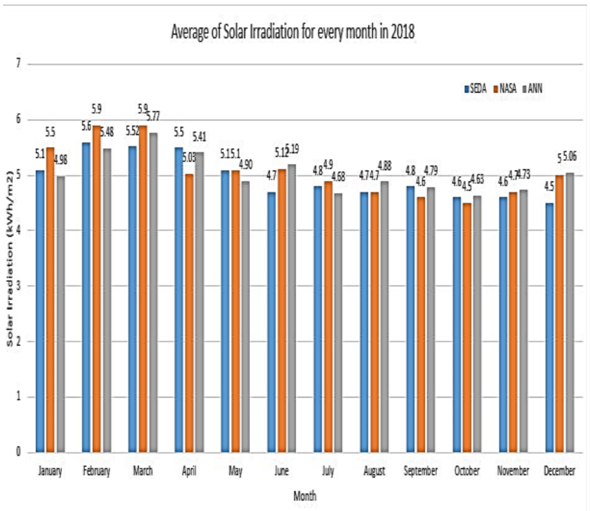

Figure 6. The comparison on average total daily solar irradiation between ANN forecasted model, SEDA and NASA for 2018

Table 1The average value of solar irradiation for every month in 2018 for forecasted, NASA and SEDA

Month	Solar Irradiation (kWh/m^2)		
	Forecasted	NASA	SEDA
January	4.98	5.5	5.1
February	5.48	5.9	5.6
March	5.77	5.9	5.52
April	5.41	5.03	5.5
May	4.9	5.1	5.1
June	5.19	5.12	4.7
July	4.68	4.9	4.8
August	4.88	4.7	4.7
September	4.79	4.6	4.8
October	4.63	4.5	4.6
November	4.73	4.7	4.6
December	5.06	5	4.5
Average	5.04	5.08	4.96

It can be clearly seen that the correlation coefficient is considerably very good where r = 0.82 (forecasted vs NASA) and r = 0.78 (forecasted vs SEDA). Thus, it can be safely said that the forecasted data is almost the same as the measured data from these 2 authorities. Additionally, results for RMSE shows a very promising finding as both results give a value that close to zero. This imply that by using ANN with MLP architecture, it can almost accurately forecast the solar irradiance of that area, in this study, Pulau Pinang. This also shows that ANN with MLP architecture has a better quality of prediction especially in solar irradiance (Voyant et al., 2017). It is further strengthened by the results obtained for MAE where both values show less than 1% for both NASA and SEDA. It can be concluded that the results of the statistical test tabulated in Table 2 shows that a good statistical behaviour had been obtained throughout the process of forecasting.

Table 2The statistical analysis between forecasted data versus NASA and SEDA

	r	RMSE (%)	MAE (%)
NASA	0.82	0.03	0.21
SEDA	0.78	0.02	0.19

This forecasting model can be further fine tune to generate a better forecasting value by adding more input parameters such as cloud condition, wind speed, sunshine duration and others. Although, the data presented is from 2018, but the overall system architecture and results obtained show that this ANN MLP delivered a promising result that potentially useful in forecasting the solar irradiance based on meteorological data.

IV. CONCLUSION

The difficulties in getting the best output performance of a PV system is challenging particularly due to an instability of solar irradiance. Although the solar irradiance is very difficult to control, by directly linking the solar irradiance towards the weather variation, it could prove a vital information for better planning and managing PV system. This study proposes an ANN with MLP architecture to continuously predict the solar irradiance by using the hourly air pressure data obtained from the meteorological department. The forecasted results then been compared with measured solar irradiance data gathered from SEDA and NASA. Results show that the overall performances of the predicting data are almost similar to data measured by SEDA and NASA. The correlation result of r = 0.82 (forecasted vs NASA) and r = 0.78 (forecasted vs SEDA) proved that this ANN MLP model is able to forecast the daily solar irradiation by using meteorological data. Hence, with a good forecasting model, a better planning and management control at PV power plant can be controlled to obtain a maximum power output.

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