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Estimation of Output Energy Performance of Fixed and Sun-Tracking Photovoltaic Panels

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Abstract
Photovoltaic (PV) is a promising solar energy technology which has been identified potentially suitable for wide scale applications in Hong Kong. The performance of PV systems is evaluated in terms of efficiency measuring based on laboratorial settings which may rarely occur in practice. This paper studies the energy performance for PV systems. On-site measurements including solar irradiance, temperatures and output energy for a PV generator were systematically recorded. An artificial neural network (ANN) was used to establish the energy efficiency and power output for various PV panel installations. The findings are reported and design implications are discussed.

Keywords – Photovoltaic; Efficiency; Artificial neural networks; Simulation

1. Introduction

There are many immediate adverse effects such as global warming, climate change and acid rain caused by fossil fuels for electricity generation [1, 2]. Renewable energy plays an important role to replace the fossil fuels and thus reduce the environmental problems. The solar energy harvested by photovoltaic (PV) technologies is recognized as sustainable and environmental friendly resource [3]. Conventionally, standalone PV systems usually demand large spatial areas for installation. Nowadays, building integrated photovoltaic (BIPV) which consists of PV panels mounted on the opaque parts of the building facades for generating electricity would be an effective technology for electricity production and building envelop heat gain reduction [5].

Traditionally, the nominal efficiency of PV system is estimated under references sunlight irradiance of 1000W/m^2, solar cell temperature of 25°C and air mass of 1.5. However, the sun positions, temperature and solar irradiance vary with the weather, season and time of a day, which make the standard test conditions rarely occur in practice. It is necessary to evaluate and estimate the performance of PV system in operation according to field measurements.

As a well-developed artificial intelligence algorithm, the artificial neural network (ANN) is effective in analyzing the inter correlation between different variables. Based on the data being measured in Hong Kong at the end of 2015, a model was developed to correlate the PV efficiency (η) with other simultaneously recorded parameters including the solar radiation on the surface of PV panel (E_{panel}, W/m^2), the temperature of PV cell ($T_{cell,}$, ℃), and the incidence angle of sunlight to the PV panel (σ, Degree) to indicate the PV operating conditions. The correlations being developed by ANN are applied to determine the year-round power output for the horizontal, vertical, tilted and sun-tracking PV systems.

2. Data Collection

The data for the ANN development were collected manually in October, 2015 in the City University of Hong Kong (22.3°N, 114.3°E). The E_{panel} was measured using the thermopile pyranometers manufactured by Kipp and Zonen. The PV system MINI-EESF/M from Edibon was used to collect the solar radiation and generate electricity (P, W/m^{-2}). The temperature of PV panel (T_{cell}) was recorded by an Infra-red thermometer. To study of PV at different directions, the panel was adjusted to tilt angles of 0°(horizontal), 22.5°, 45°, 67.5° and 90°(vertical), facing either south or south-east for non-horizontal placement. As a combination of the solar position and panel angles, the incidence angle σ was used to effectively identify the position of the sun with respect to the PV panel, which is defined as Eq. 1.

$$\sigma = \text{acos}\,[\sin\alpha_S \cos\beta + \cos\alpha_S \sin\beta \cos(\phi_S - \phi_N)] \tag{1}$$

Where α_S is the solar altitude angle, β is the tilt angle of the PV panel, ϕ_S and ϕ_N are respectively the azimuth angle of the sun and panel. All observations were made at time intervals of 1, 2 or 5 minutes. In total, 824 sets of data were collected to develop the ANN for predicting the efficiency of PV system in practice. To evaluate the year-round energy output of such PV systems, the hourly meteorological data measured by the Hong Kong Observatory (HKO) in 2013 was used. Eq. 2 was used to calculate T_{cell} using the air temperature ($T_{a,}$, ℃) and E_{cell}.

$$T_{cell} = T_a + k_r E_{cell} \tag{2}$$

According to Nordmann et al.[6], the Ross coefficient (k_r, ℃ m^2 W^{-1}) can be used to estimate the T_{cell} and Table 1 shows for different PV installations [7]. Following the procedures suggested by the CIE, the quality controls were made to remove the erroneous measurements. Finally, 3,898 datasets were accepted for the year-round study of PV energy output.

Table 1. Values of parameter k in Eq. (2)

Type of PV panel	k_r (℃ m^2 W^{-1})
Free Standing	0.0208
Flat on roof	0.026
Façade integrated	0.0538

3. Development of ANN

The artificial neural network (ANN) [8] is a data-driven, self-adaptive method that is capable of approximating complex non-liner relationships [9] between the output and other readily accessible variables (i.e. predictor). In this research, the template of a feed-forward neural network of 1 hidden layer was used as given in Fig. 1. The structure is acknowledged to be capable of giving well acceptable results for most problems.

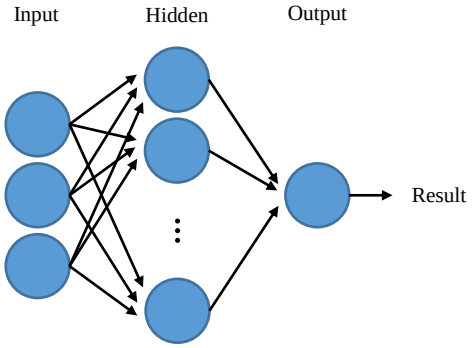


Fig.1 Structure of the Artificial Neural Network

The model of each neuron in the hidden and output layer is illustrated in Fig. 2. The outputs from the previously layer ($p_{i,1}$, $p_{i,2}$, …, $p_{i,n}$) are weighted by their correspondent weights ($w_{i,1}$, $w_{i,2}$, …, $w_{i,n}$) and summed. The sum of weighted neuron inputs plus a bias (b_i) is transferred to the activation function, which is given in Eq. 3 and Eq. 4 respectively for the hidden and output layers. The settings of equations follow the defaults of MATLAB [10]. Finally, the result is transferred to the next layer of the network.

$$f(x) = 2 / (1 + \exp (- 2x)) - 1 \quad (3)$$

$$f(x) = x \quad (4)$$

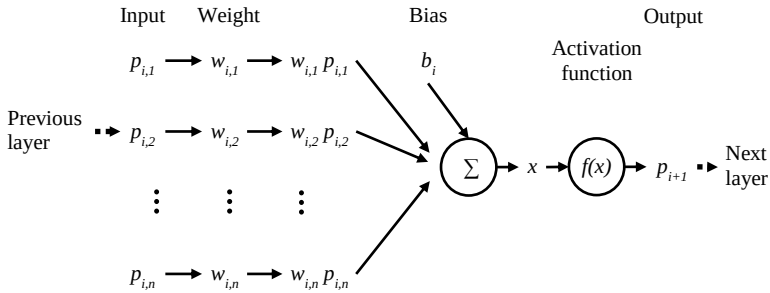


Fig.2 Model of a single neuron in hidden and output layer

The development of ANN involves the optimization of weights and biases in each neuron to give the least error of the output. In present research, the process was managed by the backpropagation algorithm based on the Levenberg-Marquardt (LM) optimization in MATLAB ANN toolbox [10]. Although the algorithm was well developed, the number of neuron (N_{hid}) in the hidden layer that controls the complexity of the neural network should be determined by the user.

For different problems, data availability and input-output relationship, N_{hid} can be quite various. It is therefore preferably to optimize the number of hidden neuron in a case by case manner. If too few neurons are used, the network may not be powerful enough to cover all the underlying features of the relationship between the input and output. When too many neurons are used, the ANN may be too powerful that "memorizing" the value of each reading by its own coefficients and structure. The inherent correlation between variables, however, cannot be satisfactorily indicated. In this regard, the networks were trained with N_{hid} set from 3 to 80.

To evaluate the expected performance of ANN with N_{hid} hidden neurons, the technique of k-fold cross validation was employed, which randomly divides the datasets into k subgroups for k rounds of training and testing processes as illustrated in Fig. 3. In each round, the neural network was developed by a unique combination of $k-1$ subgroups, which was used to predict the subgroup not being used in the neural network development. To prevent over-fitting, 30% of the datasets among the $k-1$ subgroups are employed to validate the development and the process of LM optimization will be terminated when the mean square error (MSE) of the data for validation cannot successively be reduced in i iterations. Ultimately, the predictions of each round were combined and compared with the measurements to calculate the overall MSE and coefficient of determination (R^2) to evaluate the overall performance of ANN with N_{hid} hidden neurons.

Following the default setting of MATLAB, i was set as the value of 6 to balance the alleviation of overfitting and the prevention of local minima. To reduce the uncertainty of evaluation from the random selection of training

and testing datasets while save the cost of computation, k is set to a popular size of 10 [11] in present study. Finally, the 10-fold cross validation was repeated for 1,000 times to limit the possibility of the deterioration due to the local minimum of LM optimization. The results of R^2 and the root mean square error with respect to the average of η (%RMSE) are illustrated in Figs. 4 and 5. As shown in the two figures, the model developed with N_{hid} = 12 has the maximum average R^2 and minimum %RMSE. Thus, the ANN with a structure of 12 hidden neurons was used for subsequent prediction.

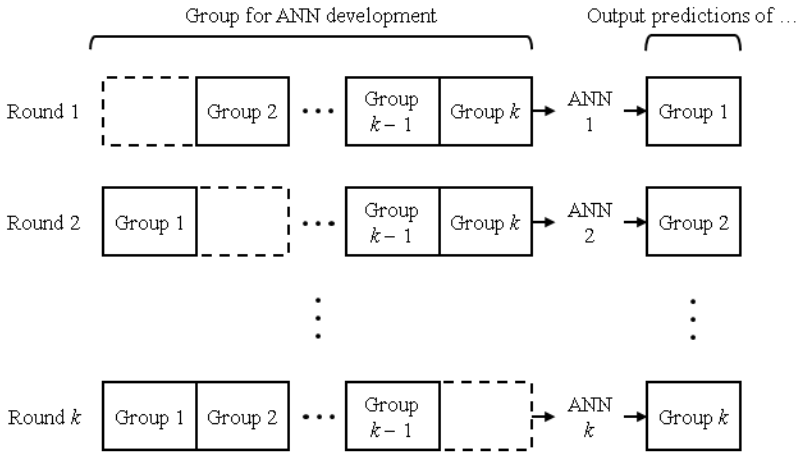


Fig.3. The k-fold cross validation

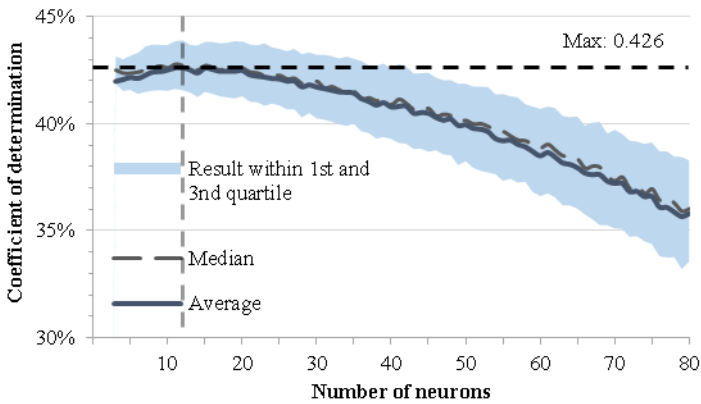


Fig.4. R^2 of the 1,000 trainings of ANN with 3 to 80 hidden neurons

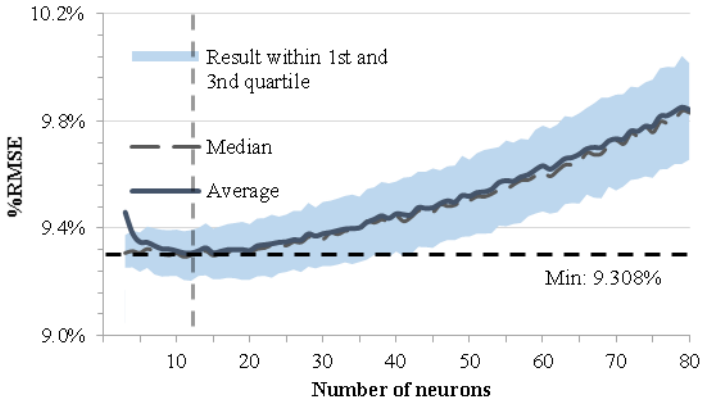


Fig.5. The %RMSE of the 1,000 trainings of ANN with 3 to 80 hidden neurons

4. The Prediction of Annual PV Performance

The installation of PV panels demands large spatial area. Without sufficient roof area, the power generation by horizontal and inclined PV panels on the flat roof may be quite limited. To analyze the long-term performance of the aforesaid PV system in different installations as given in Table 2, a year-round analysis based on the weather data of 2013 were implemented. The E_{cell} on horizontal and inclined panels are estimated by the Perez model [12].

An important prerequisite of the satisfactory ANN prediction is the newly introduced data being covered by the data for ANN development. This ensures the neural network developed by the on-site measurements is knowledgeable enough to make predictions for the new data. In this connection, a comparison was made between the cumulative frequency of occurrence (C_FOC) of the on-site measurements and the HKO 2013 database to indicate whether the on-site measurements are comprehensive. Figs. 6 to 8 depict the outcomes.

Table 2. The installations of PV systems being studied

PV installation being analyzed	k_r (˚C m^2 W^{-1})	Abbreviation in Fig.
Horizontal, free standing	0.0260	Horiz.
Inclined by 22.5˚, facing south	0.0208	Tilt 22.5_S
Sun tracking	0.0208	Sun TRK
Vertical, facing North	0.0538	Vert._N
Vertical, facing East	0.0538	Vert._E
Vertical, facing South	0.0538	Vert._S
Vertical, facing West	0.0538	Vert._W

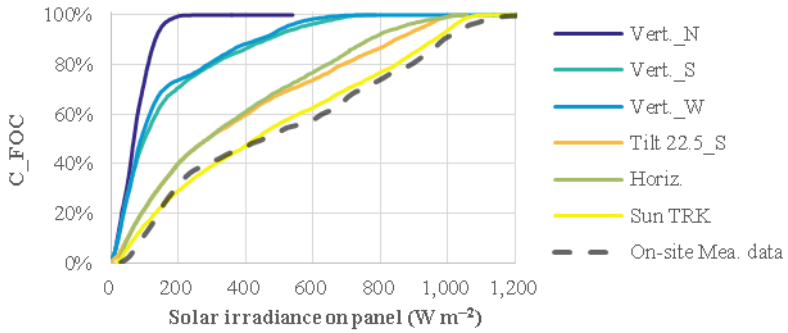


Fig.6. The C_FOC of E_{cell} for the database from on-site measurements and HKO

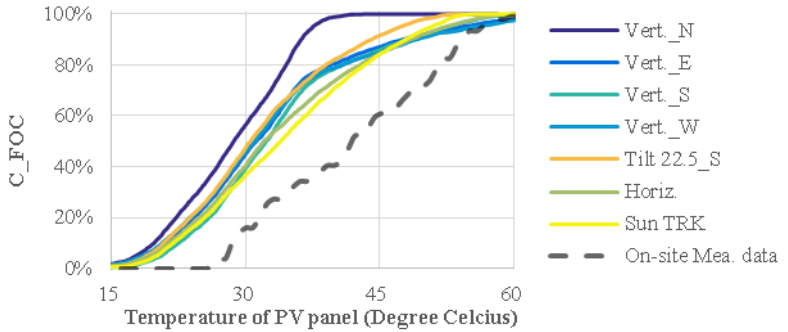


Fig.7. The C_FOC of T_{cell} for the database from on-site measurements and HKO

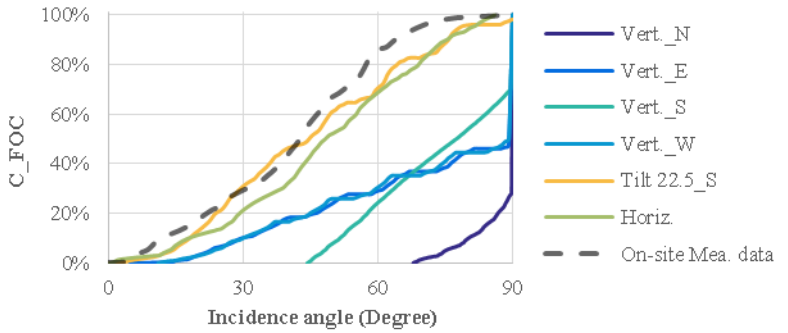


Fig.8. The C_FOC of σ for the database from on-site measurements and HKO

The figures describe the probability of data below a certain value in the database for ANN development and application. Figs. 6, 7 and 8 show respectively the E_{cell} , T_{cell} and the corresponding σ for PV panels mounted at

various inclined angles facing different orientations using data measured in 2013 and on-site measured data in 2015. It can be seen that there may be insufficient T_{cell} data below 26℃ and σ beyond 90° and less than 5℃ for the on-site measured data. Such aspects could affect the performance in non-summer months, sun-shaded PV panel and sun-tracking system, since the ANN may not get the corresponding knowledge from the database of training. To improve the results, the σ data were set 90° for the sun-shaded PV panels and 5° for the sun-tracking cases.

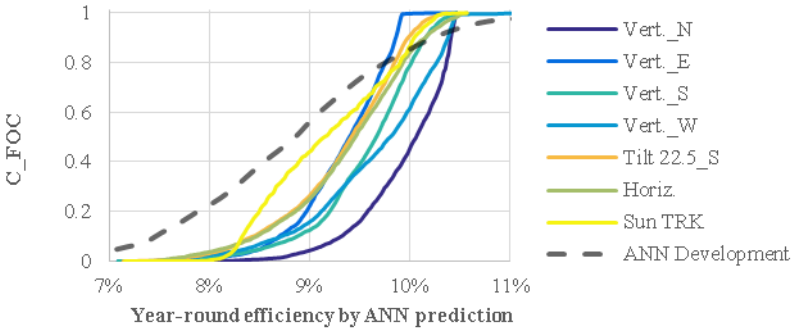


Fig.9. The C_FOC of year-round PV efficiency by ANN prediction

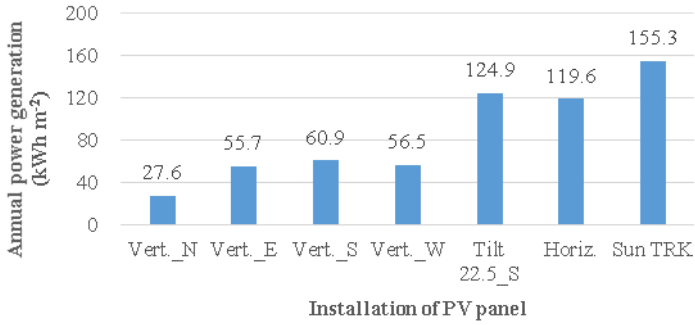
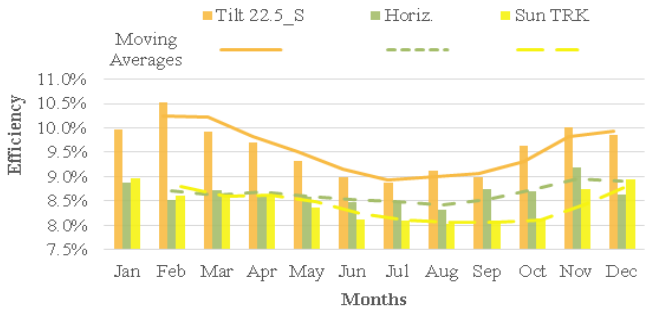


Fig.10. The year-round power generation of different PV installations by ANN prediction

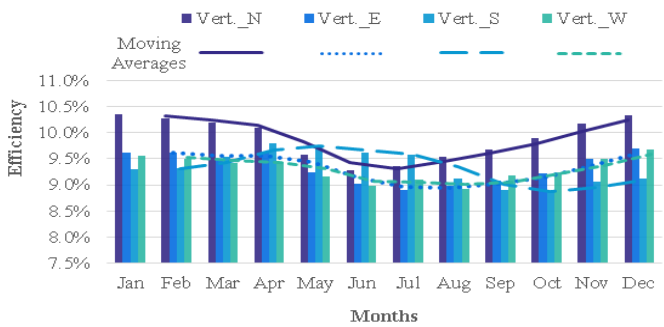
Figure 9 shows the year-round efficiency for various installations for PV panels. In general, the efficiency ranges largely between 8 and 10.5%. The north-facing vertical surface is mainly sun-shaded of lower T_{cell} and has a higher efficiency among all cases. The vertically installed PV panels were found to have slightly greater efficiencies than the other PV installations. This is probably because of the relatively lower T_{cell} of the vertical PV (more time periods being sun-shaded) alleviates the deterioration of cell efficiency due to lower temperature [7].

The year-round power outputs for different PV installations were computed and are exhibited in Fig. 10. In spite of the higher efficiency, the

year-round energy outputs for those vertical PVs are obviously less than the others. Such outcomes can be explained by the smaller solar irradiance on vertical PVs compared with the PVs for other installations. With a power output of 124.9 kWh m^{-2}, the PV panels at inclined angle of 22.5° outperform the horizontal panels. Nonetheless, more spatial areas may be required for the tilted installations to avoid the shading effects between different panels, For most of vertically installed PV panels (except for the north-facing surface), the annual energy output per square meter is roughly half of those as the horizontal and tilt installations. It means that the vertical PV may outperform the horizontal and tilted PV installations, as long as the panel areas facing east, west and south orientations are twice as the roof. The output power production by sun-tracking system is the greatest among all installations being analysed, which outpaces the tilted panels by 30.4 kWh m^{-2} corresponding to 24.3% of its power output. The benefit of energy revenue, however, may be restricted by its extra cost due to spatial area, operation power and maintenance issues.



(a)



(b)

Fig.11. The monthly average efficiency of a) horizontal, inclined and sun-tracking PV installations; b) vertical PV installations, according to the ANN prediction

The monthly average efficiencies for various PV installations were calculated and are presented in Fig. 11. It shows that the PV efficiency tends

to be greater in non-summer months for all PV installations. The reduction of PV efficiency from Jun to September for most PV installations is possibly due to the relatively larger T_{cell} causing by the high T_a and E_{cell} in the hot and long day-length summer in Hong Kong.

5. Conclusions

An artificial neural network was built to predict the efficiency (η) of photovoltaic panels in practical operation conditions. The model was applied to the year-round hourly weather data of Hong Kong to estimate the hourly efficiency and energy output of different PV installations. It was found that although the efficiency of horizontal and sun-tracking PVs has less frequency of occurrence at high level comparing the vertical ones, their annual power generation is 120W/m^2, which is more than twice of the vertical PVs. The monthly average PV efficiency in summer is generally less than that in winter due to the higher T_a and T_{cell}.

6. Acknowledgment

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