# Three Layered Feed-Forward Neural Network based Estimation of Output Power and Energy on Photovoltaic (PV) Modules

Syafaruddin, Wardi, Gassing, Zaenab Muslimin, Zulkifli Tahir, Engin Karatepe and Takashi Hiyama, *Senior Member, IEEE*

***Abstract*—The paper presents the application of three layered feed-forward neural network for predicting the output power and energy generation of photovoltaic (PV) modules. The neural network structure is designed to determine the estimated output power of PV modules based on the input of open circuit voltage and cell temperature. The open circuit voltage is one of the electrical parameters output from PV modules based *I-V* characteristic models from Sandia National Laboratory. The estimated energy of PV generation is obtained by connecting the estimated output power with simple mathematical integration process. The proposed method is tested to PV modules from different manufacturers and technologies, such as monocrystalline Silicon, Cadmium Telluride (CdTe) and triple junction amorphous Silicon. The simulation results show the high accuracy prediction compared to the conventional data measurements.**

***Index Terms*—PV modules, TFFNN, estimated power, estimated energy, real-time simulator.**

## I. Introduction

SOLAR energy usage and penetration have recently increased significantly due to global environmental reasons and sustainable energy development. The solar energy technology can guarantee more secure power sources which are air and noise pollution-free, have longer lifetime and require low maintenance [1]. The technology also offers very competitive price and better reliability. The worldwide annual growth capacity has averaged a little more than 30% since the last decade [2]. As a result, solar energy is used in a wide range of applications; from rural energy electrification in [3] to satellite communication in [4]. However, it still remains a big challenge for the global community to maximize the use of solar energy.

One of the main challenges is the output power and energy PV modules are unpredictable due to variations in irradiance level and cell temperature. Therefore, it is inevitable to estimate the output power and energy of PV modules. Daily, monthly and yearly predictions are very important for the planning operation of the entire power systems when small-scale of PV modules are installed in the system. In the stand-alone and hybrid systems, the estimated output power is very useful for optimizing the operating condition of equipments, such as battery, inverter and charger controller [3], [5]. Moreover, the scheduling of other generation units in hybrid systems can be precisely determined for the sake of supply reliability and reduction in the investment cost [3]. Meanwhile, the estimated output energy of PV modules will be beneficial to the investment calculation of solar energy system [6].

The estimated output power of PV modules has been presented in some papers. In [7], the overall performance of PV systems, such as PV and inverter efficiency and overall system efficiency have been predicted using TRNSYS simulation software. This method is successful in predicting the output power of large PV system in the long term performance. The application of artificial neural network (ANN) has also been used to estimate the maximum power generation from PV module by using the environmental information, such as, irradiance level, temperature and wind velocity [8]. The benefits of using artificial neural network are that there is no requirement for knowledge on internal system parameters; requires less computational effort and provides a compact solution for multivariable problems [9].

In this paper, the application of ANN was utilized to predict the power generation of PV modules based on the variation in the irradiance level and cell temperature. In the neural network training process, the open circuit voltage based *I-V* characteristic model and the cell temperature are used as the input and the power at maximum power point based *I-V* characteristic model is used as the target output. For obtaining the estimated output energy, an integrator block is added in the estimated power which is an output of the ANN. To justify the

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*Proceedings of 3rd Makassar International Conference on Electrical Engineering and Informatics (MICEEI), 28 November-1 December 2012, Makassar Golden Hotel (MGH), Makassar, Indonesia*

*Supported by IEEE Indonesia Section, IEEE APS/MTT Indonesia Joint Chapter, and IEEE Communication Society (Comsoc) Indonesia Chapter ISBN 978-602-8509-18-3*

accuracy of the proposed method, several types of PV modules from different manufacturers and technologies (for instance, SIEMENS SM-55 PV module with monocrystalline silicon technology, First Solar FS-50 with Cadmium Telluride (CdTe) and USSC US-21 with Triple Junction Amorphous Si (a-Si-3) technologies) were used. All simulation results were verified in real-time simulator.

## II. Basic Configuration of the Proposed System

In general, the proposed system consists of two main blocks, viz. the PV module and the ANN block. The electrical characteristic outputs of PV modules based on the *I-V* characteristic model can be obtained as a result of the change in the irradiance level ($E$) and cell temperature ($T_c$). Three of the electrical parameters, such as open circuit voltage ($V_{oc}$), current and voltage at maximum-power point ($I_{mp}$ and $V_{mp}$) were used in the neural network training process. Although the short circuit current ($I_{sc}$) is denoted as "unused" in the network, but this parameter is very important to determine $V_{oc}$, $I_{mp}$ and $V_{mp}$. Meanwhile, the open circuit voltage ($V_{oc}$) and cell temperature ($T_c$) are specified as the input in the ANN block. The output from ANN block is designated as the estimated power, whereas the output from PV module block is denoted as the measured power. The estimated energy and measured energy are obtained by connecting the integrator block to the estimated power and measured power respectively. Further details on the basic configuration of the proposed system shown in Fig.1 will be explained in the following sections.

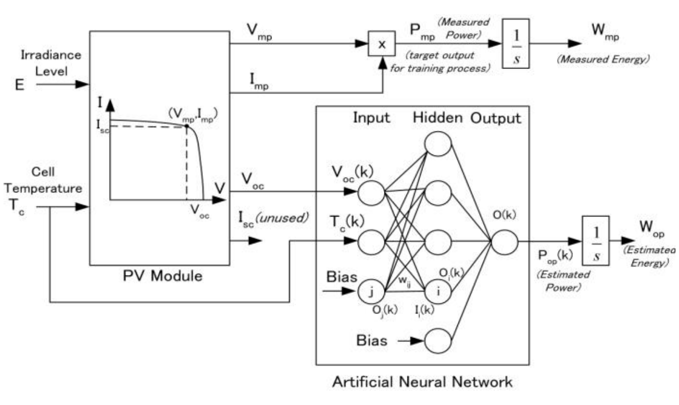


Fig. 1. Configuration of the proposed system

### A. PV Module Configuration

There are four output electrical parameters of PV modules that can be derived from *I-V* characteristic model as the irradiance level ($E$) and cell temperature ($T_c$) change. These output parameters are short circuit current ($I_{sc}$), open circuit voltage ($V_{oc}$), current at maximum-power point ($I_{mp}$) and voltage at maximum-power point ($V_{mp}$). In this study, the *I-V* characteristic was developed based on the mathematical model of Sandia's PV Module Electrical Performance Model [10], [11].

The short circuit current ($I_{sc}$) equation of PV module based on this model is presented as follows:

$$I_{sc} = I_{sco}\, f_1(AM_a)\left(\frac{E_b\, f_2(AOI) + f_d\, E_{diff}}{E_o}\right)(1+\alpha_{I_{sc}}(T_c - T_o)) \quad (1)$$

where

- $I_{sco}$ — $I_{sc}$ at E = 1000 W/m$^2$, AM$_a$ = 1.5, T$_c$ = 25$^o$C, AOI = 0$^o$
- $f_1(AM_a)$ — empirically determined polynomial relating spectral influence on $I_{sc}$ to air mass
- $f_2(AOI)$ — empirically determined polynomial describing AOI influence on $I_{sc}$
- $E_b$ — beam component of irradiance on module
- $f_d$ — fraction of diffuse irradiance used by module
- $E_{diff}$ — diffuse component of irradiance on module
- $\alpha_{Isc}$ — normalized temperature coefficient for $I_{sc}$
- $T_c$ — temperature of cells inside module
- $T_o$ — reference temperature for performance model, 25$^o$C

Equation (1) can be simplified by assuming the AM$_a$ function is equal to 1.0 and combining the beam and diffuse components into single component irradiance, denoted by the irradiance level ($E$); as presented in (2).

$$I_{sc} = I_{sco}\left(\frac{E}{E_o}\right)(1+\alpha_{I_{sc}}(T_c - T_o)) \quad (2)$$

where

- $E_o$ — reference irradiance, 1000 W/m$^2$

Other equations, such as open-circuit voltage ($V_{oc}$), current at maximum-power point ($I_{mp}$), and voltage at maximum-power point ($V_{mp}$), are presented in (3) to (5).

$$V_{oc} = V_{oco} + N_s\,\delta(T_c)\ln(E_e) + \beta_{V_{oco}}\,E_e\,(T_c - T_o) \quad (3)$$

$$I_{mp} = I_{mpo}\,(C_0\,E_e + C_1\,E_e^{\,2})(1+\alpha_{I_{mp}}(T_c - T_o)) \quad (4)$$

$$V_{mp} = V_{mpo} + C_2\,N_s\,\delta(T_c)\ln(E_e) + C_3\,N_s\,(\delta(T_c)\ln(E_e))^2 + \beta_{V_{mpo}}\,E_e(T_c - T_o) \quad (5)$$

where

- $V_{oco}$ — $V_{oc}$ at $E_e$=1, $T_c$=$T_o$
- $I_{mpo}$ — $I_{mp}$ at $E_e$=1, $T_c$=$T_o$
- $V_{mpo}$ — $V_{mp}$ at $E_e$=1, $T_c$= $T_o$
- $\alpha_{Imp}$ — normalized temperature coefficient for $I_{mp}$
- $\beta_{Voco}$ — temperature coefficient for $V_{oc}$ at 1000 W/m$^2$
- $\beta_{Vmpo}$ — temperature coefficient for $V_{mp}$ at 1000 W/m$^2$
- $C_0$, $C_1$ — empirically determined coefficients relating $I_{mp}$ to irradiance

$C_2$, $C_3$ empirically determined coefficients relating $V_{mp}$ to irradiance
$N_s$ number of cells in series in a cell-string

The effective irradiance ($E_e$) and the thermal voltage per cell $\delta(T_c)$ are presented in (6) and (7), respectively.

$$E_e = \frac{I_{sc}}{I_{sco}(1+\alpha_{I_{sc}}(T_c - T_o))} \tag{6}$$

$$\delta(T_c) = \frac{nk(T_c + 275.15)}{q} \tag{7}$$

where

$n$ empirically determined diode factor for each cell in module
$k$ Boltzmann's constant, $1.38066.10^{-23}$ J/K
$q$ elementary charge, $1.60218.10^{-19}$ coulomb

The measured power ($P_{mp}$) is calculated by the multiplication between (4) and (5), while the measured energy ($W_{mp}$) is obtained by the integration of the $P_{mp}$. Both these equations are shown in (8) and (9).

$$P_{mp} = I_{mp} V_{mp} \tag{8}$$

$$W_{mp} = \int_t P_{mp} dt \tag{9}$$

TABLE I
SPECIFICATION OF PV MODULES

| PV module specifications | SIEMENS SM-55 | First Solar FS-50 | USSC US-21 |
|---|---|---|---|
| Materials | c-Si | CdTe | a-Si-3 |
| Vintage | 1999 (E) | 2001 (E) | 1999 (E) |
| Area (m$^2$) | 0.425 | 0.72 | 0.356 |
| $N_s$ | 36 | 116 | 11 |
| $I_{sco}$ (A) | 3.45 | 1.08 | 1.59 |
| $V_{oco}$ (V) | 21.7 | 85 | 23.8 |
| $I_{mpo}$ (A) | 3.15 | 0.87 | 1.27 |
| $V_{mpo}$ (V) | 17.4 | 58 | 20.9 |
| $\alpha_{Isc}$ (°C$^{-1}$) | 0.00055 | 0.00065 | 0.00085 |
| $\alpha_{Imp}$ (°C$^{-1}$) | -0.00008 | 0.0022 | 0.0012 |
| $\beta_{Voco}$ (V/°C) | -0.087 | -0.22 | -0.098 |
| $\beta_{Vmpo}$ (V/°C) | -0.089 | -0.098 | -0.052 |
| $n$ | 1.086 | 1.3 | 3.77 |
| $C_0$ | 1.02 | 1.073 | 1.096 |
| $C_1$ | -0.02 | -0.073 | -0.096 |
| $C_2$ | 0.08818 | -1.25 | -1.14162 |
| $C_3$ (V$^{-1}$) | -8.434 | -18.544 | -2.89115 |

(AM=1.5; 1000W/m$^2$; 25$^o$C)

Three types of PV module with different technologies were used in this study; viz. SIEMENS SM-55 PV, First Solar FS-50 and USSC US-21. SIEMENS SM-55 PV module which is built on monocrystalline Silicon technology can deliver high efficiency output power under reduced light condition by using pyramidal textured surface [12]. The First Solar FS-50 with CdTe technology is recommended when high output voltage is desired. This module uses very thin layers of compound semiconductor material with low temperature coefficients which provides for a cost-effective and greater energy production system [13]. The last module (USSC US-21) is equipped with the latest new triple junction technology. Instead of containing glass, this module is composed of encapsulated polymer inside a rigid anodized aluminum frame [14]. The PV module specification is presented in the Table I.

Based on the *I-V* characteristic model, each PV module has unique electrical response characteristics to the variations in irradiance levels and cell temperature. Fig. 2 shows that the $P_{mp}$ of all PV module types increases proportionally with the variation in the irradiance levels. The difference is only at the maximum output power based module in the high irradiance level. At an irradiance level of 1000 W/m$^2$, both SIEMENS SM-55 and First Solar FS-50 PV modules reach the $P_{mp}$ at about 50 W. For the same irradiance level, the $P_{mp}$ achieved by the USSC US-21 is only about half the value attained by the other two types.

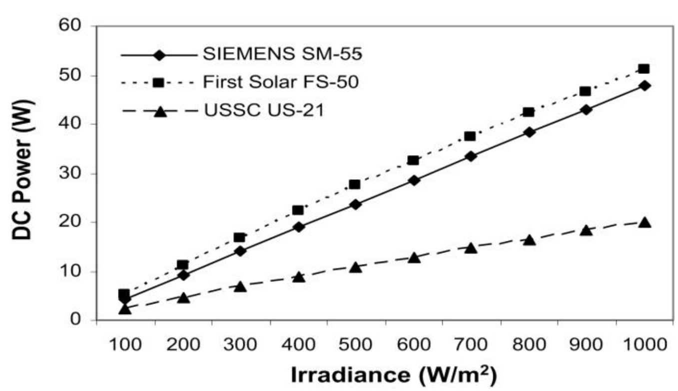


Fig. 2. Power at maximum-power point for PV modules at $T_c$ =50$^o$C

## B. ANN based Estimated Output Power of PV Modules

In the proposed configuration, a three-layer feed forward neural network was used: an input, a hidden and an output layer to determine the estimated output power ($P_{op}$) of PV modules. The input layer consists of three nodes for the open circuit voltage ($V_{oc}$), cell temperature ($T_c$) and a bias signal of 1.0. In this study, the open circuit voltage was derived from (3), while the cell temperature was arbitrarily determined in the range of 10$^o$C and 65$^o$C. The number of nodes of hidden layer depends on the minimum error obtained during the training process. The output layer provides the estimated output power.

In the hidden layer, the sigmoid function is utilized for the input-output characteristics of the nodes. For each node $i$ in the hidden and output layers, the output $O_i(k)$ is given as follows:

$$O_i(k) = \frac{1}{1+e^{-I_i(k)}} \tag{10}$$

The term $I_i(k)$ in (10) is the input signal to node $i$ at the $k$-th sampling. The input $I_i(k)$ is given by the weighted sum of the input nodes as follows:

$$I_i(k) = \sum_j w_{ij}(k).O_j(k) \tag{11}$$

In (11), $w_{ij}$ is the connection weight from node $j$ to node $i$ and $O_j(k)$ is the output from node $j$.

To identify the estimated output power accurately, the connection weights $w_{ij}$ must be calculated using typical patterns called the training process.

In the training process, a set of input-output patterns for neural network is required. During the training, the connection weights $w_{ij}$ are modified recursively until the best fit is achieved for the input–output patterns based on the minimum value of the sum of the squared errors. The equation of the sum of the squared errors is described as:

$$E = \sum_{k=1}^{N}\left(t(k)-O(k)\right)^2 \tag{12}$$

where $N$ is the total number of training patterns, $t(k)$ is the $k$-th target output from the output node and $O(k)$ is the computed value. Initially, the value of connection weigths $w_{ij}$ is set to random values. For all the training patterns, the error function is evaluated and the connection weights $w_{ij}$ are updated to minimize the error in (12).

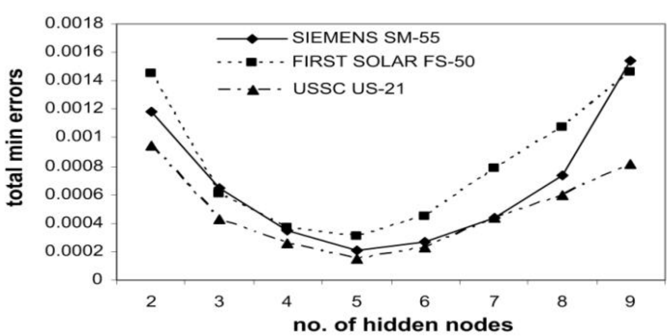


Fig. 3. Number of hidden nodes based on the total minimum errors.

The input for training data criteria is the open circuit voltage ($V_{oc}$) and cell temperature ($T_c$). The $V_{oc}$ can be obtained from (4) with the given input of irradiance level between 100 and 1000 W/m$^2$ (with an increment of 50) and the cell temperature from 10$^o$C to 65$^o$C (with an increment of 5$^o$C) to the PV module. The reason for selecting these data due to the *I-V* characteristic model proposed by Sandia National Laboratories is only valid for these data range. Again, the data range of $V_{oc}$ used as the input must also be less than or equal to the value of $V_{oco}$ in Table I. The output target is the power at maximum-power point ($P_{mp}$) which can be calculated in (8). There are about 200 training sets for the training process due to these input-output criteria. During the training process, the learning rate and the momentum are specified to 0.2 and 0.85, respectively.

The number of hidden nodes is selected based on the total minimum errors during the training process. Fig.3 shows the results of training process related to the total minimum errors and number of hidden nodes. The total minimum errors of all PV module types are achieved when the number of hidden nodes is 5. It means that the connection weights $w_{ij}$ of all modules have the same dimension.

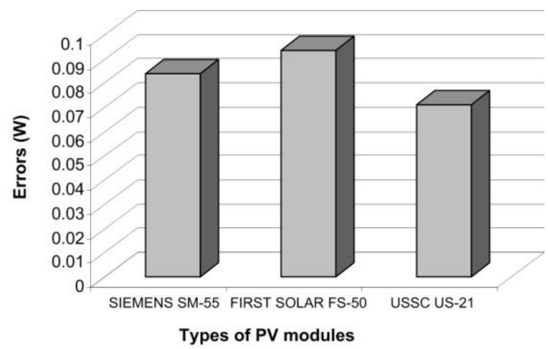


Fig. 4. Average errors between $P_{op}$ and $P_{mp}$

The neural network training process has significant correlation with the *I-V* characteristic of each module. The First Solar FS-50 PV module with different pattern of PV module had more difficulty in obtaining the total minimum errors. As a result, the First Solar FS-50 PV module showed slight increase in the average error between the estimated output power ($P_{op}$) and the output target, denoted as $P_{mp}$ compared with the SIEMENS SM-55 and USSC US-21 PV modules. Verification the total minimum errors results in Fig.3 can be seen in Fig. 4.

## III. Simulation Results and Discussion

The estimated output power and energy of PV modules were obtained by feeding in irradiance level and cell temperature as input from 5 a.m to 8 p.m on a daily basis to all types of PV modules. Both irradiance level and cell temperature were changing rapidly and were seen to be quite unpredictable due to environmental factors. The fluctuation of these variables can be seen in Fig. 5. The simulation results



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show that the application of ANN for predicting the output power and energy of PV modules is quite precise. Fig. 6, 7 and 8 show the estimation results related to the output power and energy compared with the empirical measurement for SIEMENS SM-55, First Solar FS-50 and USSC US-21 PV modules, respectively.

Estimation of output power and energy of PV systems in the planning operation is very important since the output of the system depends on the environmental condition. Some benefits can be obtained by knowing the output power and energy of PV module early.

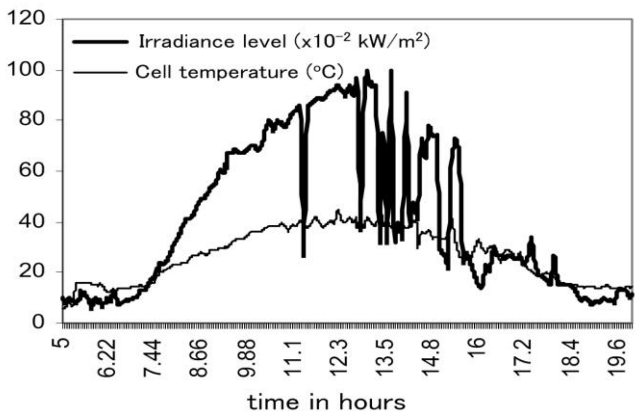


Fig. 5. Daily condition of irradiance level ($E$) and cell temperature ($T_c$).

There are two common operations of PV system in the grid, either in the form of stand-alone or hybrid systems. In the stand -alone and hybrid PV systems, the estimated power will be very useful to optimize the operation of equipment, such as battery and inverter. The optimized operation of battery in this case is related to the accuracy of charging and discharging schedules in order to prolong the life time of the battery and to reduce the low-load engine operation. In terms of inverter operation, the prediction of the inverter output can be done since the inverter efficiency is the function of output power of PV system.

Another advantage of predicting the output power of PV system in the hybrid operation is the availability of accurate scheduling for other units of generation, for instance the diesel engine and hydro power. Accurate prediction and coordination between units will improve the supply reliability and reduce the cost investment. At the end of the day, the estimated output power of PV system in hybrid system will contribute to reduce the fuel consumption, to optimize the number of operating hours and to reduce the maintenance cost for other units.

Similar to the benefits of predicting the output power, the estimated output energy of PV system can be beneficial to determine the estimated electricity tariff in certain power grid. The electricity cost which is measured in currency/kWh can be estimated as money saving when the PV system is connected to the grid. Moreover, the benefits of solar energy investment which is specified as gain or loss can be figured out by using information of estimated output energy.

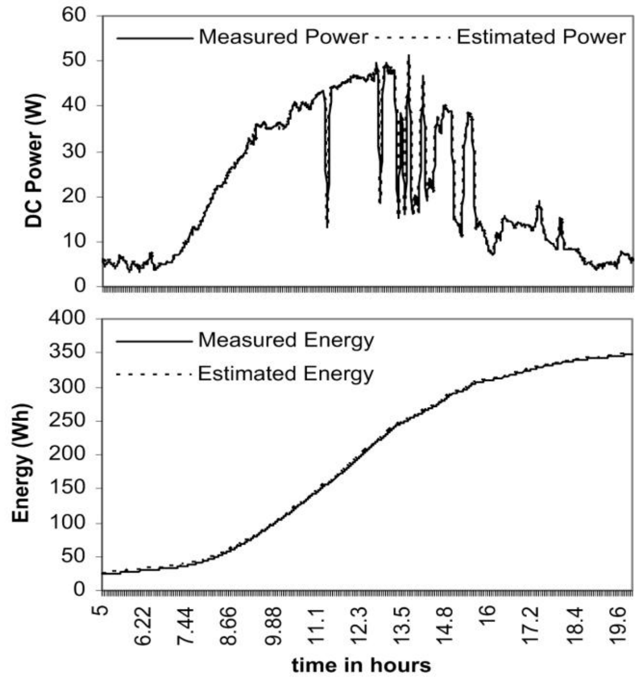


Fig. 6. Measured and estimated output power and energy for SIEMENS SM-55.

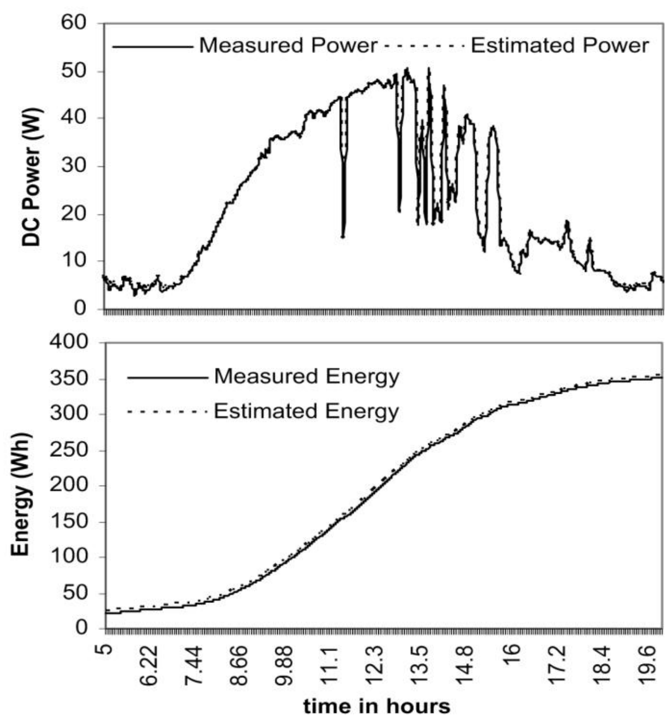


Fig. 7. Measured and estimated output power and energy for First Solar FS-50.

Proceedings of 3rd Makassar International Conference on Electrical Engineering and Informatics (MICEEI), 28 November-1 December 2012, Makassar Golden Hotel (MGH), Makassar, Indonesia

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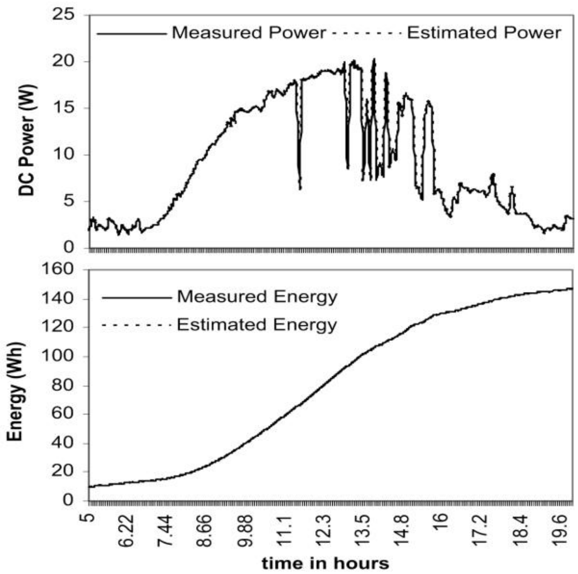


Fig. 8. Measured and estimated output power and energy for USSC US-21.

## IV. CONCLUSIONS

The accuracy of the proposed ANN for predicting the real-time output power of PV generation has been presented in this paper. ANN was used to estimate the optimum output power of PV module with the input of open circuit voltage based *I-V* characteristic model and cell temperature. The ANN estimator is able to estimate the output power on PV modules of different technologies and from different manufactures for every variation in irradiance level and cell temperature, even without the PV module hardware. Consecutively, the estimated output energy can also be found by connecting the integrator to the estimated output power. Some discussions are presented to support the benefits of the proposed method. An extensive works are still required for further verification.

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