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Optimal Power Tracker for Stand-Alone Photovoltaic system using Artificial Neural Network (ANN) and Particle Swarm Optimisation (PSO)

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Abstract. In recent years, many intelligent techniques and approaches have been introduced into photovoltaic (PV) system for the utilisation of free harvest renewable energy. Generally, the output power generation of the PV system rely on the intermittent solar insolation, cell temperature, efficiency of the PV panel and its output voltage level. Consequently, it is essential to track the generated power of the PV system and utilise the collected solar energy optimally. Artificial Neural Network (ANN) is initially used to forecast the solar insolation level and followed by the Particle Swarm Optimisation (PSO) to optimise the power generation of the PV system based on the solar insolation level, cell temperature, efficiency of PV panel and output voltage requirements. This paper proposes an integrated offline PSO and ANN algorithms to track the solar power optimally based on various operation conditions due to the uncertain climate change. The proposed approach has the capability to estimate the amount of generated PV power at a specific time. The ANN based solar insolation forecast has shown satisfactory results with minimal error and the generated PV power has been optimised significantly with the aids of the PSO algorithm.

Key words

Photovoltaic system, Optimal Power Tracking, Power Generation, Artificial Neural Network, Particle Swarm Optimisation.

1. Introduction

Photovoltaic (PV) system is known as green energy for its power and technology which have enormously evolved over the last decades [1], unlike the conventional power generating system which has been using in most countries. The dependency on conventional power generating based on natural resources is high due to the increasing demand on electrical energy. Unfortunately, natural resources are limited as it equally increasing the market price. For that reason, many studies and researches on solar energy are increasing as to replace the natural resources for power generation purposes.

Malaysia is a one of the tropical country which is located entirely on the equatorial region. The solar insolation receives in Malaysia is averagely ranging from 4.21 kWh/m^2 to 5.56 kWh/m^2 [2]. The average ambient temperature has generally remains uniform throughout the year ranging from 26 °C to 32 °C [2]. Hence, the abundance sunshine throughout the year receives in Malaysia spurs the interest of harnessing solar energy.

A detailed data is required as it designates an interest for potential location with the highest solar energy measurement [3]. Due to the demand growth in solar energy, a proper modelling and forecasting of solar insolation is required. This method maximise the usage of solar energy [4] as it improve the operation control and energy optimisation [5] in PV system. Potential location with highest solar measurement does not guarantee the maximum PV power generated. This is because the performance of PV system is influenced by the cell temperature, fault level of PV array and voltage of the power output. Henceforth, power tracking methods are important because it minimises the problem of low conversion efficiency of the PV system at various conditions.

Maximum Power Point Tracker (MPPT) is one of the methods that have been implemented in PV applications as it enhances its conversion efficiency which relies on the operating voltage of the array [6]. Three-point weight comparison method has been introduced [6] in perturbation and observation algorithm for MPPT. Whereas [1] and [7] applied Artificial Intelligence (AI) such as Genetic Algorithm (GA), Artificial Neural Network (ANN) and Particle Swarm Optimisation (PSO) into the MPPT controller by searching the maximum power point of the PV module.

Although MPPT has advantage in control algorithm, that advantage becomes a disadvantage in terms of cost and capacity. In addition, the complexity of the overall system consumes more power [8]. Therefore, Momoh, J.A proposed another technique on optimal power tracking using ANN to forecast solar insolation and GA to optimise the power generation of the PV system at a specified voltage [4]. This method is not complex and it is suitable for mounted stationary PV panel corresponding to this research.

Henceforth, this paper features an important criterion to optimise power for the PV generator based on solar insolation prediction and characteristics of PV panel. The priority of these criteria is determined using two methods. Artificial neural network (ANN) is used to forecast the solar insolation level due to its ability to solve multivariable problem with less knowledge of internal system parameter [9]. The proposed PSO optimise the power generated at a specified voltage level under various operation circumstances. PSO would be a useful tool to optimise the PV generated power due to its well-known method for optimising nonlinear function based on swarming social interaction [1].

2. PV System Architecture and Procedure for Optimal Power Tracking

The schematic diagram of the PV system is shown in Fig. 1. The experiment takes place by logging the solar insolation fall horizontally on the PV panel as well as the charging voltage and current at no load. The solar data logger is tilted at the same angle as the solar panel while the power logger is tapped at 1 as shown in Fig. 1.

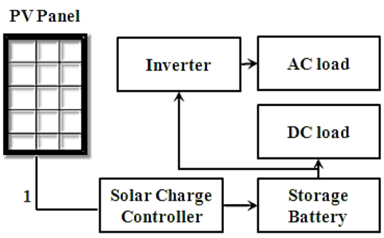

Fig.1. PV panel deployment architecture

Fig. 2 depicts the work procedure of this research and the parameters selection for the PV power generation optimisation process. The actual solar insolation level is measured for a period of time followed by the ANN based solar insolation level forecast. The forecasted results are then applied into PSO in order to evaluate the best power optimisation at a specified voltage level.

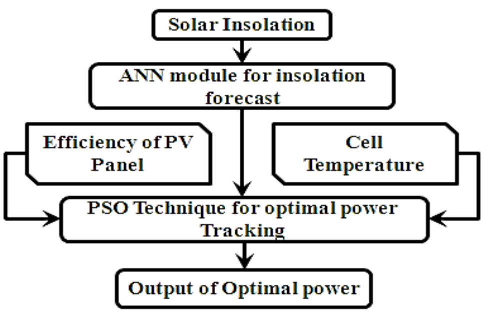

Fig.2. Block Diagram for Optimal Power Tracking

3. Data Collection

Essential data such as solar insolation, charging current and PV generated voltage have been measured for 60 days, from July 9th 2011 to September 9th 2011. The data are only been collected for 12 hours per day from 7am to 7pm under tropical climate conditions where this is the period for the sun radiates the most. Fig. 3 shows the daily average solar insolation level along the period of 60 days. Fig. 4 to Fig. 6 show the experimental mean values of the 12 hourly solar insolation level, charging voltage and current, respectively.

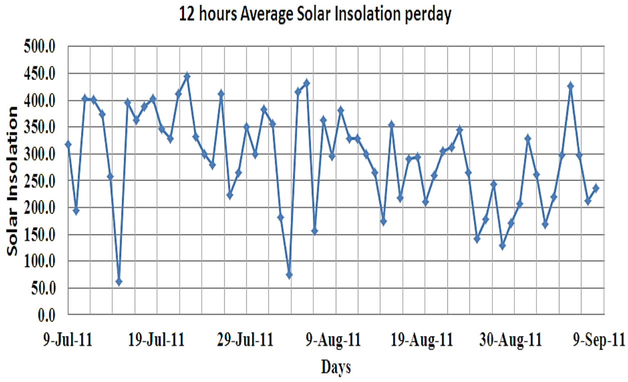

Fig.3. Daily average insolation level

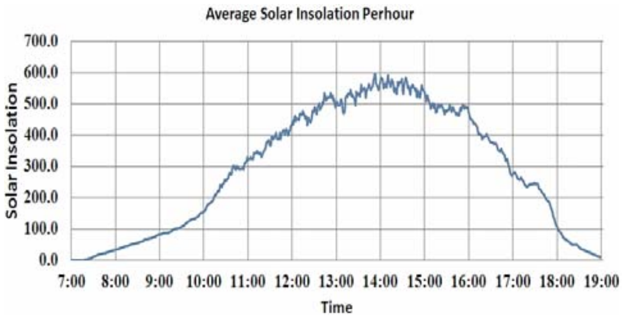

Fig.4. Average 12 hourly solar insolation level

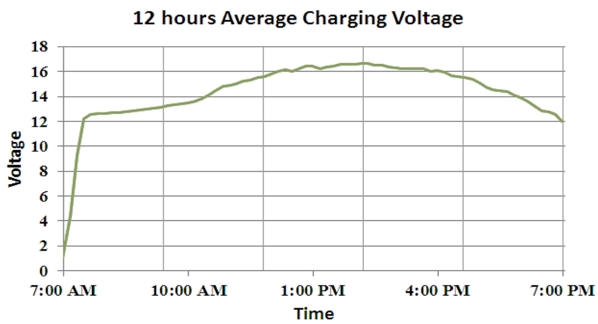

Fig.5. Average 12 hourly charging voltage

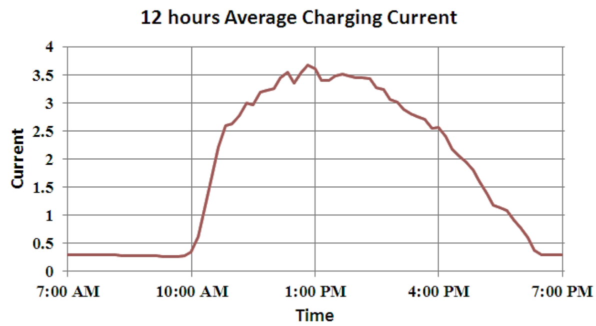

Fig.6. Average 12 hourly charging current

4. PV Module Modelling Using MATLAB

This paper adopts the simplest PV equivalent circuit model represented in MATLAB environment as given in Fig. 7 [10]. The comparisons of the model parameters with the manufacturer data sheet, SUNSET AS 80M model are summarised in Table I. The performance of the PV module depends much on the ambient conditions such as insolation level and cell temperature, as depicted in Fig. 8 and Fig. 9, respectively.

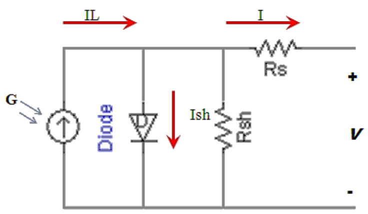

Fig.7. Circuit diagram of the PV model

Table I. Comparison of Parameters of the adjusted model and SUNSET AS 80M data sheet values at standard condition

Technical Specification	Data Sheet	Model
Rated power P_{max}	80	80
Rated current I_{MPP}	4.60	4.60
Rated voltage V_{MPP}	17.4	17.4
Short circuit current I_{SC}	5.10	5.10
Open circuit voltage V_{OC}	21.8	21.8
No. of series cell (N_s)	36	36
Series resistance, R_S		0.00866
Shunt resistance, R_{Sh}	**Not Specified**	Neglected
Diode Ideality Factor		1.45

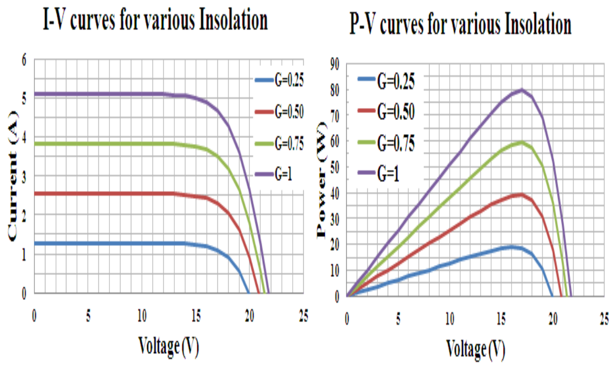

Fig.8. Model characteristics of SUNSET AS 80M, solar module at different insolation levels (T=25 °C)

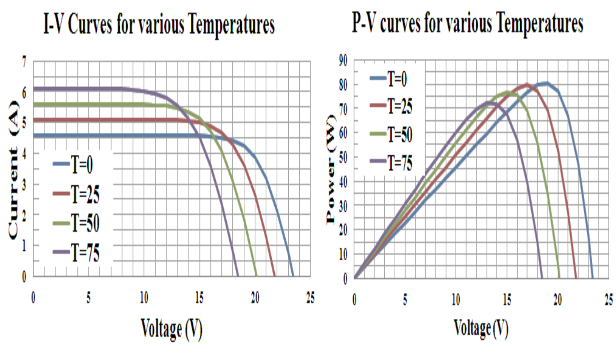

Fig.9. Model characteristics of SUNSET AS 80M, solar module at different temperatures (G=1000 kW/m^2)

5. Solar Insolation Level Forecasting using ANN

ANN has been widely used in many applications especially in solar energy estimation field [11]. Multi-Layer Perceptron (MLP) is commonly used in modelling and forecasting [9] due to its well-known feed-forward structure [12]. The MLP structure presented in this research comprises of an input, output and a hidden layers. This structure imitates the basic function of the human brain as it receives inputs, combine them and produce final output result [12]. The input data are divided into training, validation and test sets. The input and output data are normalised in the range between -1 and 1. Fig. 10 shows the MLP input parameter with the output produces the next day 12 hours solar insolation.

MLP network has various connection styles and learning algorithms as it is adapted to its structure and convergence time. Back-propagation is a popular supervised learning algorithm [11] and it is used in this research due to its ability to adjust the weights for the network in producing a desired output. Without supervised learning algorithm, the weights are not adjusted to the target data as the desired output is unachievable.

Activation function refers to the output relation of the network to the input based on the input activity level. Sigmoid activation function is widely used due to its non-linearity function whose output lies in between 0 and 1 [13]. It is used in between each hidden layers. "Tansig" activation function is used at input-hidden layer whereas "Purelin" activation function is used at hidden-output layer. According to the analysis done in [14], "Tansig" and "Purelin" are the best structure due to its minimal mean square error (MSE).

MLP network is simulated in MATLAB environment. The Levenberg-Marquardt algorithm is used as a numerical tool to minimise the error during training process. The best MLP structure depends on the best activation function and number of neurons in the hidden layer. Trial and error method determine the results of a suitable number of neuron in each model.

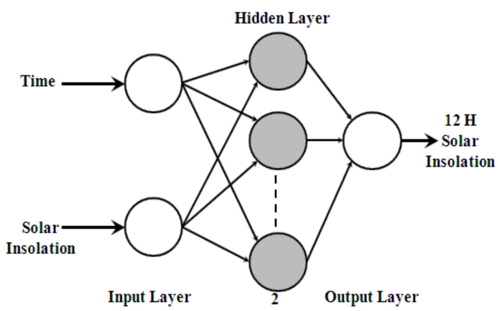

Fig.10. MLP network for 12-Hours forecast

The forecasting results in two different weather conditions are shown in Table II. In order to evaluate the obtained results, different parameters are calculated for each prediction. Correlation coefficient, *r* indicates the adjacent predicted and measured data. MSE provides information on long-term model performance which specifies the average deviation between the predicted values to the corresponding measure values. As the coefficient of determination, R^2 approaches 1 and MSE approaches zero this signifies the solution of the problem provides the most accurate solution [11]. Table II shows the prediction results with minimal error as highlighted. The forecasted results for sunny and rainy weather on July 11th (2011) and July 15th (2011) are 0.2% and 0.09%, respectively as shown in Figs. 11 and 12.

Table II. Number of nodes corresponding to the MLP network performance on July 11th 2011 (Sunny) and July 15th 2011 (Rainy)

No. of Nodes	Sunny			Rainy		
	R2	MSE	r	R2	MSE	r
1	0.994	0.003	0.997	0.921	0.0075	0.974
2	0.978	0.01	0.991	0.905	0.0092	0.953
3	0.986	0.006	0.993	0.956	0.0044	0.981
4	0.988	0.006	0.994	0.942	0.0064	0.977
5	0.982	0.013	0.984	0.921	0.0076	0.967
6	0.977	0.01	0.997	0.968	0.0031	0.988
7	0.978	0.009	0.998	0.963	0.0038	0.991
8	0.976	0.01	0.993	0.948	0.0049	0.984
9	0.997	0.002	0.999	0.959	0.0042	0.989
10	0.984	0.006	0.996	0.92	0.008	0.963
15	0.977	0.01	0.996	0.993	0.0009	0.997
20	0.978	0.01	0.995	0.98	0.0023	0.992
25	0.982	0.008	0.993	0.945	0.006	0.987
30	0.985	0.007	0.997	0.942	0.0067	0.983

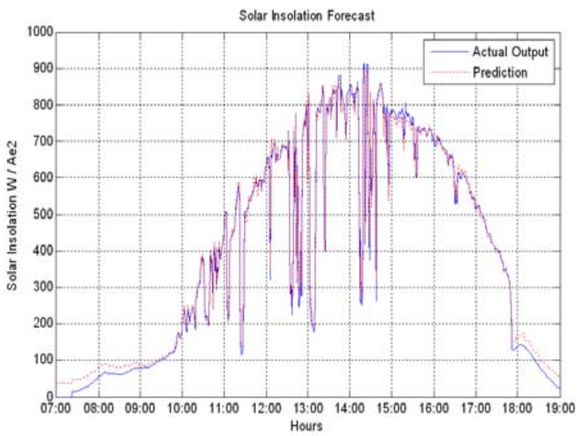

Fig.11. Solar insolation measured and prediction on July 11th 2011 (sunny) using MLP model 9

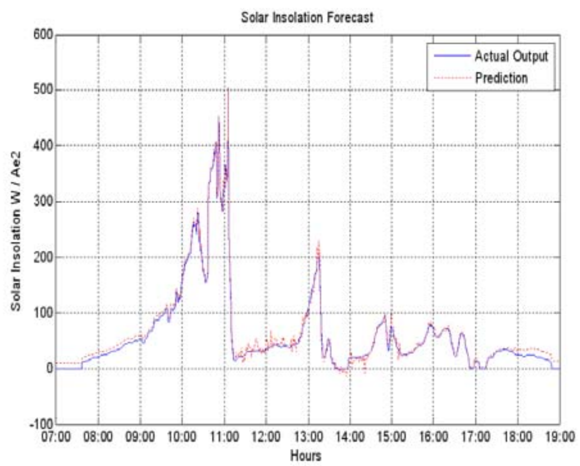

Fig.12. Solar Insolation measured and prediction on July 15th 2011 (rainy) using MLP model 15

6. The Proposed PSO Algorithm for Optimal Power Tracking

Particle swarm optimization (PSO) is an optimisation technique based on social behaviour of organism such as birds flocking, fish schooling and bee swarming. This technique was introduced by James Kennedy and Russell Eberhart to optimise nonlinear functions [15].

PSO is proposed in this research to optimise the power generation for the PV system under various operating conditions such as different insolation levels and cell temperatures. Various PV panel efficiencies are tested in order to determine the effectiveness of the power generation optimisation using PSO technique. The procedure of the developed PSO algorithm is presented in the flowchart given in Fig. 13, where the algorithm is divided into six key steps as follows:

1. Initialisation of swarm position with random guess for the searched solution $P_{PV\ optimal}$.
2. Evaluation of the objective function of the corresponding initialised $P_{PV\ optimal}$. The objective function is chosen to be the m order polynomial curve fitting of the power and voltage characteristics of the PV panel.
3. Updating swarm position and velocity according to Eqns. (1) and (2) [16].
4. Evaluation of the updated population.
5. Check if all iterations are carried out.
6. Output the global best result of $P_{PV\ optimal}$ that satisfied the objective function.

The $P_{PV\ optimal}$ is computed from the PSO in order to determine the optimal power generated from the PV system. The computed $P_{PV\ optimal}$ is based on the operating condition of the overall PV system. The operating conditions are then fed into the algorithm to compute the objective function and updating both swarm velocities and positions.

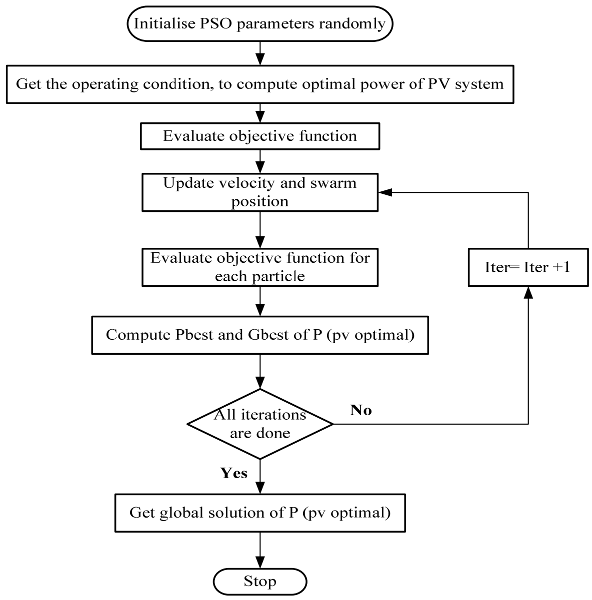

Fig.13. Flowchart of PSO algorithm

$$V_i^{k+1} = \omega V_i^k + c_1 r_1 (Pbest_i^k - X_i^k) + c_2 r_2 (Gbest^k - X_i^k) \quad (1)$$

$$X_i^{k+1} = X_i^k + V_i^{k+1} \quad (2)$$

where,

v_i^k velocity of individual, I at iteration k ,
ω inertia weight parameter ,
c_1, c_2 acceleration coefficients ,
r_1, r_2 random numbers between 0 and 1 ,
X_i^k position of individual, I at iteration k ,
$Pbest_i^k$ best position of individual, I at iteration k ,
$Gbest_i^k$ best position of the group until iteration k ,

$$\omega = \omega_{\max} - \frac{\omega_{\max} - \omega_{\min}}{Iter_{\max}} \times Iter \quad (3)$$

where,

$\omega_{\max}, \omega_{\min}$ initial and final parameter weights,
$Iter_{\max}$ maximum iteration number,
$Iter$ current iteration number.

A. PSO Input Parameter

The selected input parameter of PSO comprises operating conditions such as insolation level, efficiency of the PV arrays and cell temperature. The details are explained as follows.

Insolation Level: In general, the insolation level rating for a PV panel is ranges from 0-1.0 kW/m^2 in terms of per unit value.

Temperature: The PV module panel rating is specified at a cell temperature either degrees or in Kelvin.

PV efficiency: The range of the rated value starts from 0.1 to 1.0 as each value defines the efficiency percentage for PV panel.

Order of polynomial: the order specifies for the polynomial curve fitting of the power and voltage characteristics of the PV panel.

The proposed artificial intelligence algorithms will be integrated into one package in order to perform the optimal power tracking of PV stand-alone system using MATLAB software.

B. Problems Formulations

Each computed value is used in PSO is to determine the best result of $P_{PV\ optimal}$. Each calculation is explained in the following.

1. Objective function: Power generated by PV system

This paper proposes polynomial curve fitting technique in obtaining the optimal generated power of the PV system. This technique has been applied in many applications due to its best approximation corresponding to the actual result. By using the curve fitting method under the power and voltage characteristics of the PV panel, the coefficient of the m order polynomial is obtained. Subsequently, the power generated of the PV system can be approximated by an m order polynomial as a function of the panel voltage. The panel voltage at a given specific time can be referred to Fig. 5. Given the operating conditions such as solar insolation level, cell temperature, fault level of PV panel and the output voltage, the optimal power tracking PV system can be expressed as follows:

$$P_i(v_i) = \sum_{i=1}^{m} a_i v_i \quad (4)$$

Subject to $0 \leq v_i \leq v_{i,0}$

where

a_i : Polynomial coefficient which is obtained through curve fitting model
m : Order of the polynomial chosen
$v_{i,0}$: Open circuit voltage of the i solar panel
P : Power generated of the system

Table III and Fig. 14 show the approximation power using curve fitting. The power and voltage characteristics of the PV panel curve are computed at the 700 W/m^2 and 28 °C. By using the curve fitting, the coefficient is obtained to calculate the power at a specific voltage, i.e. 17.1V. From Table III, the calculated maximum power is obviously on the 6th order of polynomial.

Table III. Approximation power with the increasing number of polynomial

Number of Polynomial, n	Power, (W)
1	-4.737
2	28.48
3	55.93
4	55.39
5	54.98
6	56.26
7	55.59
8	55.58
9	55.63
10	55.44

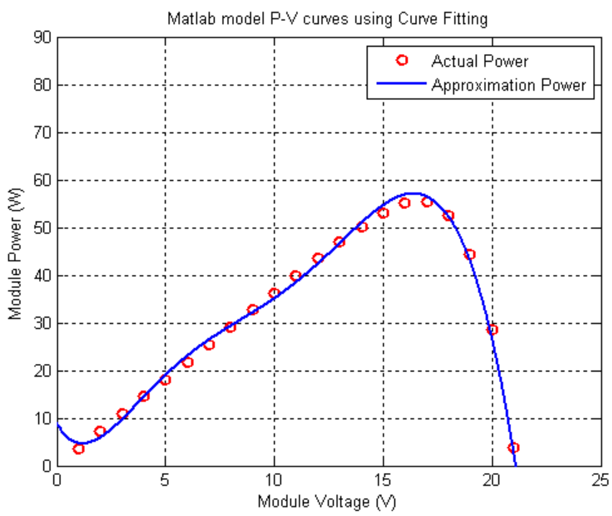

Fig.14. 6th order polynomial using curve fitting method

The total generated power by the PV system can be calculated according to the following equation:

$$P_{PV}(V_i) = \sum_{i=1}^{N} P_i(V_i) \quad (5)$$

where N is the number of parallel-connected solar panels. Subsequently, the total generated power by the PV system is subtracted with the measured charging power gaining from Figs. 5 and 6. Thus, this has explained that the PV system operation is much more practical.

2. Efficiency of PV module

The efficiency of the PV module will be multiplied to each PV module in order to determine the efficiency of the optimal power generation. The efficiency of the PV module can be formulated as follows:

$$\eta = \frac{P_{\max(no\min al)}}{P_{\max(ref)}} \times 100 \quad (6)$$

$$P_{\max(no\min al)}(G,T_C) = V_{OC}(G,T_C) \times I_{OC}(G,T_C) \times FF \quad (7)$$

$$FF = \frac{P_{\max(ref)}}{I_{SC(ref)} \times V_{OC(ref)}} \quad (8)$$

where

G: Solar Insolation rating at 0 – 1000 W/m^2

T_C: Cell Temperature

ref: Standard condition at G=1000 W/m^2 and T_C = 25°C

FF: Fill factor

V_{OC}, I_{OC}: Open circuit Voltage and Current of PV Module, respectively

I_{SC}: Short Circuit current of PV module

7. Conclusion

An integrated scheme for optimal power tracking has been proposed in this paper. With the aid of this method, the PV system is able to perform and to enhance the production of the electrical energy at an optimal solution under various operating conditions. As a result, a precise estimation of the PV power generation is known through the optimisation technique as it is to curb the conversion efficiency of the PV system. Likewise, it gives opportunity for any designer to deploy a stationary mounted rooftop PV system to fully harvest the solar energy at any potential location. Due to the offline optimisation technique, this method has its limitation. In contrast to the online optimisation technique, this method requires to store the collected data in a database which is normally done manually. Although this method has its setback, yet it can be modified in the future for online application purposes. The proposed method can become a useful tool in any possible applications regarding to economic power dispatch. The integrated scheme of optimal power tracking can be included into a control system as it can optimally dispatch power to the random loads based on the estimated power generated. Thus, this improves the power dispatch of the PV generator in order to avoid any electrical breakdown as the load fluctuates.

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