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Modeling Single Diode PV using Particle Swarm Optimization (PSO) Techniques

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ABSTRACT: The photovoltaic (PV) systems have grown in popularity in recent decades as one of the most cost-effective renewable energy resources that convert solar energy to electric energy. A reliable and accurate PV system model design is required to estimate the performance of a PV system before it is deployed. The proposed model is based on the single diode model (SDM), which gives a comprehensive simulation of the influence of irradiance and temperature on PV module parameters following the characteristics I-V or P-V requires of five parameters. The particle swarm optimization (PSO) technique to characterize the equivalent accurate PV module is used to extract model parameters by finding the optimum solution. The approach of parameter estimation and evaluation and model assessment in Matlab. The simulation results show that the proposed technique works well for modeling both the solar cell and the module.

Keywords – *Solar cell, PV, Single diode, Parameter estimation, PSO.*

1. Introduction

Due to population growth, the growing need for energy and electricity demand is continuously increasing. Hence, global warming has become a significant problem for the world as the impacts of economic development industrialization become increasingly obvious and reach almost every corner of the globe. Currently, renewable energy sources are abundantly recognized as profitable energy resources according to their widespread availability and cleanliness (Rathore and Panwar 2009). Therefore, renewable energy sources have prompted researchers to create more efficient and environmentally friendly technologies. Solar, wind, wave, nuclear, tidal, geothermal, and other renewable energy generation methods are considered the most extensively used renewable energy sources (Peinado Gonzalo, el, García Márquez 2020). Solar photovoltaic (PV) systems have grown in popularity in recent decades as one of the most cost-effective renewable energy resources due to their ubiquitous availability and cleanliness, as well as their potential to help address energy challenges. Like a thermal plant, the PV technology's focus is directly transforming solar energy into electrical energy in these applications (Lemes, Elmer, and Corrêa 2019).

Nonetheless, unlike in the past, the cost and performance of PV systems are highly dependent on power plants, environmental variables such as solar radiation and temperature, and the electrical properties of the cells. The extraction of solar module parameters is critical for performance analysis, efficiency computation, and maximum power in a PV system. (Cubas, el, and De Manuel 2014).

Despite the fact that solar energy is abundant and at the forefront, its expansion is restricted by partial shading, erratic nature, high initial cost, and the need for expensive storage. However, the prediction of PV panel functioning characteristics is crucial and requires a forecast of PV system performance prior to energy production systems' installation and maintenance standards. Thus, detailed modeling, analytics methodologies, simulation analysis, and evaluation of solar PV systems are essential to compete with new technologies and improve efficiency for long-term viability and sustainability (Lemes, *el*, and Corrêa 2019). Modeling also aids in comprehending the functioning principle and operational parameters of a solar PV system under various atmospheric circumstances (Venkateswari and Rajasekar 2021). Regarding the issue, valuable research applied different analytical approach-based computations to derive the PV parameters and examine the features of PV technology. The most often used models are accurate mathematical modeling for a PV system in understanding the behavior of PV system features to replicate the behavior of genuine PV cells, i.e. to fit their observed current-voltage (I-V) curves (Jordehi 2016). Further, some methods proposed heuristic approaches such as Genetic Algorithm (GA), and Particle Swarm Optimization (PSO), especially for low populations (Bana and Saini 2017) (Li, Gong, and Gu 2021). Most of these studies examine the techniques encountered during the operation and maintenance of PV systems, taking into account their inspection and various power operating modes (Walker 2001). However, most prior studies have focused on operational problems or how degradation processes influence the PV systems in different applications without detailing the approaches' procedures and structures.

This paper outlines the analyses and mathematical modeling of the single diode PV model (SDM). Given the importance of optimum PV parameter estimation for PV model design, the paper discusses the problem formulation and parameter selection for the proposed optimization approach. PSO is also used to derive PV cell characteristics from parameter estimates for real-world operating conditions with varying insolation and temperature. It enables the use of a low population, which has the potential to expedite the process of convergence. On the other hand, preventing early convergence allows for a global search of parameter solutions inside a particular solution space, thus making the initial parameter selections more resilient.

The rest of this paper is organized as follows: Section 2 reviews the literature used throughout the model for PV design. Section 3 explains the principle of PV technology and parameters estimation for PV modules. The mathematical formulation of PV and system models is detailed in Section 4. Simulation and results discussions are indicated in Section 5, and finally, the conclusion is stated in Section 6.

2. Literature Review

This section recognizes the innovations and efforts made in recent years in parameter estimation methods. According to the literature (Venkateswari and Rajasekar 2021), analytical and meta-heuristic optimization methodologies are two commonly used strategies for addressing and determining unknown parameters to address this challenge. Most analytical approaches were established by applying a range of operating settings in conjunction with widely accessible manufacturer datasheet information to improve a solar PV characteristic prediction. In comparison, the meta-heuristic technique allows for a broad parameter search region in order to obtain the best estimation using each data point on the

estimated IV curve to be compared to the actual values. On the other hand, when operating near optimal levels, it can occasionally experience accuracy and convergence issues.
A heuristic technique Mean-Variance Method Optimization (MVMO), has been demonstrated in (Lemes, Elmer, and Corrêa 2019). The methodology implemented multimodel for damping controllers, power flow calculations.). However, the MVMO outperforms standard heuristic approaches such as (GA) and PSO), especially for small-scale populations having other than one local solution in the space of solutions.

The models in (Bana and Saini 2017) and (S1876610217326504 n.d.) presented a PSO approach to characterize the equivalent electrical model of a solar cell. The PSO approach is used to extract and investigate a model with either three, five, or seven parameters by finding the global minimum solution in a given time frame. Conducting a system analysis by simulation is possible with a suitable photovoltaic model and correct parameters, which is more cost-effective and reliable than performing experiments in the real system. Furthermore, it can analyze the given generation efficiency, power, and flexibility to interruptions, among other things, using these simulations (Omer, Fardoun, and Hussain 2016).
Many optimization algorithms for extracting parameters and helping in the construction of an accurate PV model investigate the issues faced in the construction of the target function for optimization and the extraction of correct values. Over the last few decades, academics have concentrated on creating an analytical and numerical technique for parameter extraction.
As a solar energy generator, photovoltaic arrays have a considerable variety of factors that impact PV array performance, which cause the array's operation conditions to fluctuate or fault. These variables include ambient temperature, solar insolation and control, fault analysis and modeling, as well as internal parameter extraction. Accordingly, various ways to extract and optimize the internal physical characteristics of the solar cell have been proposed. The authors of (Maniraj and Peer Fathima 2021) presented a heuristic technique called BMO based on natural bird breeding habits. The approach has been tested to select objective functions and outperformed many other comparable metaheuristic algorithms. Moreover, an improved hybrid-based (GA-PSO) technique is used in this study (Saravanan and A. Panneerselvam 2013) to propose an improved model approach for single diode PV models. The main goal is to extract realistic PV model parameters for simulator designers, which will aid them in developing a better PV model in Matlab/Simulink.

3. Selection Parameters of PV Cell Modules

The photovoltaic (PV) system is a renewable energy source that transforms solar radiation into electricity with an economic outlook and low maintenance requirements. Nonetheless, the solar cell, built of semiconductor materials, serves as the fundamental building component of photovoltaic technology (Rathore and Panwar 2009). PV solar energy generates electricity in PN junctions ranging from hundreds of watts to megawatts by utilizing the device effect on semiconductor materials based on the flow of electrons in particular materials when subjected to electromagnetic radiation (sunlight). Several approaches have been developed to better understand the physical mechanisms at work within the solar generator, such as cell, array, and module. Like PV cells, solar cells are typically coupled in series, parallel, or mixed configurations to create appropriate voltage and power, stored, or given to the grid. A PV array is a structure be created by connecting multiple modules in various configurations to yield any voltage and current combination required. However, analytical techniques can solve this challenge since they are simpler and need less data (usually found in the datasheet) to determine the many characteristics that define the properties of solar panel behavior (Kumari and Geethanjali 2018).

PV power systems are quantitatively classified based on their crystalline structure and materials, or their power generation capabilities, whether stand-alone or grid-connected, at the following level performance of PV systems, including solar radiation and temperature, electrical characteristics of modules, and environmental factors. Also, ideality factor, photocurrent, saturation current, shunt, and series resistances for a single or double diode model are essential parameters for circuit model I-V lumped connection characteristics. These parameters are utilized in modeling to investigate the system's behavior(Venkateswari and Rajasekar 2021) (Cubas, Pindado, and De Manuel 2014).

The maximum power point technique is crucial in improving solar PV and highly beneficial from model selection used to increase overall efficiency, even though installing a PV panel is high. Solar energy is largely dependent on various environmental circumstances, like temperature (*K)* and irradiance (W/m^2) causes variations in the output of solar panels. However, simulating a solar panel under changing irradiation levels to establish the features of solar PV and minimize inefficiency loss. Besides, precise assessment of each parameter extraction is crucial in the modeling process.

Regardless of model type, estimating optimum parameters to determine the behavior under various operating situations is unavoidable to depict actual PV performance to maximize cost and profits. Incorrect parameter selection can result in significant model development issues, while appropriate parameter selection will lead to good PV system design. However, because the energy efficiency of PV systems is tied to solar radiation, events such as shadowing in various cases may slow down power output (Venkateswari and Rajasekar 2021). Moreover, the root means square error (RMSE) factor is used to evaluate each method's efficiency. A lower RMSE method is considered more successful in assessing solar PV parameters. In all cases, parameters and RMSE values are taken into account independently to help users understand how different solar PV panels grow and deteriorate. Various coefficients for assessing aging should be included in the future (Omer, Fardoun, and Hussain 2016).

4. Mathematical Formulation of PV Models

Typically, the single diode model (SDM) and the double diode model (DDM) is the most often utilized models used for modeling for PV system (Ibrahim and Anani 2017)(Carrero, Amador, and Arnaltes 2007). Both models are a circuit-based representation of the solar device junction that usually corresponds to the junction of the P-N diodes in the absence of sun irradiation. Compared to a single model, the DDM is more precise than the single-diode model, but it is also more complicated to implement due to the additional parameters: I_{sd} *and* n. However, analytical techniques for PV modeling use system parameters such as V_{CO}, I_{SC}, V_{mpp}, and I_{mpp}. Hence, solving such equations is difficult, time-consuming, and necessitates numerous efforts to obtain an exact solution.

4.1 Single Diode Model (SDM)

PV's equivalent reference circuit model for a single diode model (SDM) of a solar cell is shown in (Fig.1). PV module model provides an excellent balance of simplicity and precision. The model consists of a current source in shunt with a single diode and three parameters, photogenerated current I_{ph}, diode saturation current I_0, diode ideality factor A, representing the recombination of current component and diffusion, the diode current I_{diode}, and shunt resistance current I_{sh}, to form the five parameters jointly.

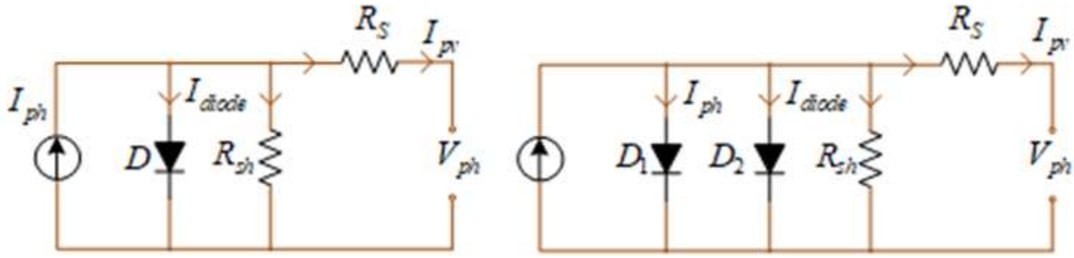

Figure 1. a) The single diode modes (SDM), b) The double diode model (DDM).

Further, the model considers a shunt resistance R_{shunt} and a series resistance R_S representing the semiconductor layers around the cell's edges (i.e. leakage current) represented a current source parallel to a diode material resistance, and internal resistance is taken into account solar illumination (Omer, Fardoun, and Hussain 2016). The notations used in this paper are shown in Table 1.

Table 1. Model Notations.

Symbole	Notation
K	Boltzmann constant ($1.3806\times10^{-23}\,J/K$)
I_{ph}	The photogenerated current
I_0	Diode saturation current
I_{sh}	Shunt resistance current
I_{diode}	Diode current.
R_{sunt}	Shunt resistance
R_s	Series resistance
q	Elementary charge
G	Actual Irradiance
T_0	Operating temperature in Kelvin
N_{Cell}	Number of connected cells
R_{Total}	Equivalent Parallel Resistance

The formula for the SDM's or terminal current current-voltage relationship is as follows after applying Kirchhoff's voltage low, the mathematical expression for current is calculated as follows:

$$I_{diode} = I_{sh}[\exp(\frac{V+IR_s}{n_s V_t}) - 1] \tag{1}$$

$$I_{shunt} = \frac{V+IR_s}{R_{sh}} \tag{2}$$

Depending on the load constraints, the respective modules are either coupled in series to enhance voltage levels or linked in parallel to boost current levels. As a result, the number of cells linked in series (n_s) will be proportional to the output current:

$$I_{out} = I_{ph} - I_{sd}[\exp(\frac{V+IR_s}{n_s V_t}) - 1] - \frac{V+IR_s}{R_{shunt}} \tag{3}$$

Figure (2) illustrates the I-V characteristic curve), and the multi-diode model is provided for (TDM) design contains a large number of diodes linked in series or parallel. The overall behavior of the DDM PV model can be characterized by the maximum and minimum boundaries of the five parameters: $[I_{ph}(0 to 1A), I_{sd}(0, to 1\mu A), R_{shunt}(0 to 100\Omega), R_s(0 to 0.5\Omega), n(1,2)]$.

$$I_{oupv} = I_{ph} - (I_{d1} - I_{d2}) - I_{sh} \tag{4}$$

$$I_{d1} = I_1[\exp(\frac{v_{pv} + i_{pv}R_s}{a_1 V_t}) - 1] \tag{5}$$

$$I_{d2} = I_{02}[\exp(\frac{v_{pv} + i_{pv}R_s}{a_2 V_2}) - 1] \tag{6}$$

$$I_{sh} = \left(\frac{v_{pv} + i_{pv}R_s}{R_{sh}}\right) \tag{7}$$

Extracting accurate parameters from PV models is crucial for evaluating PV cell performance, refining PV cell design, and optimizing manufacturing processes and quality control. The material characteristics of solar cells dictate that they perform best at low temperatures. As the temperature rises over the working temperature, the cell efficiency falls. A significant portion of incident insolation is lost as heat, leading to high cell temperatures. Therefore the open-circuit voltage $V_{mp(T)}$, circuit current I_{SC} , and short circuit current, and $I_{mp(T)}$ at a particular temperature are used to calculate the impact of temperature on maximum power $P_{mp(T)}$. Therefore the current at a given temperature $I_{SC(T)}$ is given by (Xu and Wang 2017):

$$I_{SC} = R_{Total}\{I_{pv} - I_0[\exp(\frac{I_{SC(T)} + R_{shunt}}{aNV_{t(T)}}) - 1]\} \quad (8)$$

$$I_{Tr} = I_{ph}N_p - I_{sd} = N_p[\exp(\frac{VN_p + IR_sN_s}{nN_sN_pV_t}) - 1] - \frac{VN_p + IR_sN_s}{R_{sh}N_s} \quad (9)$$

The product of maximum current and voltage (V-I) determines the maximum as follows:

$$P_{Total(T_0)} = \frac{R_pV_{mp(T_0)}}{R_{shunt} + R_p}\{I_{pv} - I_0[\exp(\frac{V_{mp(T_0)} + I_{mp(T_0)}R_{shunt}}{aNV_{t(T_0)}}) - 1] - \frac{V_{mp(T_0)}}{R_p}\} \quad (10)$$

Further, the Root Mean Square Error (RMSE) has been used to evaluate the difference between the experimental data (I-V curve), and the model results RMSC is:

$$(\frac{1}{N}\sum_{i=1}^{N}(f(V_{Tr}, I_{Tr}, x)^2))^{1/2} \quad (11)$$

4.2 System Model

Particle swarm optimization (PSO) is a population-based swarm intelligence technique that focuses on optimization in continuous areas of social activity. Furthermore, the PSO parameters are as follows: the acceleration coefficients are c1 and c2, and the present movement is generated by a difference between [0, 1], two random numbers, commonly known as the inertia factor, which ranges between min and max for the population size (model n.d.). The PSO process starts by randomly seeding a swarm of each individual called a particle represented in problem space by a d-dimensional vector $x_i = (x_{i1}, x_{i2}, ..., x_{id})$ for $i = 1, 2, ..., N$ (*N* is the population size). Its performance is assessed using the preset fitness function. The algorithm is driven by personal experience (*Pbest*), global experience (*Gbest*), and the particles' present movement to predict the particles' future locations in the search space. The dynamical interaction of individual particles determines the movement direction of each particle as a result; each particle is generated at random as a potential solution, it is put in d-dimensional space. The i^{th} particle's velocity $v_{i1}, v_{i2}, ..., v_{iN_p}$ is described as a shift in its location. The algorithm completes the optimization by pursuing the best personal solution of each particle and the swarm's overall best value.

Following the model in (Chin, Salam, and Ishaque 2015), to represent the photovoltaic system, all constants in the above equations may be found by looking at the manufacturer's ratings of the PV array followed by the measured or reported I-V the array's. The model integrates easily with PSO, and a single diode model is used. The temperature dependency, the diode quality factor, and five diode characteristics were added to the model by varying irradiance to evaluate performance under dynamic environmental conditions. The procedure first identifies the region in which to search for the value of each parameter, and then those values must be normalized between 0 and 20. The PSO constraint PV modules' parameters like ideality factor, series resistance, and parallel resistance with

$A_{(\min)} < A < A_{(\max)}, R_{S(\min0} < R_S < R_{S(\max)}, R_{P(\min)} < R_P < R_{P(\max)}$, the objective function is evaluated as:

$$f(A, R_S, R_P, T) = f(I_{SC}) \tag{12}$$

Table 2. The proposed hybrid PSO algorithm

Algorithm 1	
Input	Define the model parameters
1	Use the objective function to categorize the current set of individuals
2	Initialize the PSO Parameters
3	Calculate the population's mean and variance for each parameter
4	Generate a particular individual using an objective function to select the optimal particle.
5	Update the new to the population and their objective function.
6	Update G_{best} and P_{best}
7	Go to step 2.
8	Check algorithm convergence
Output	The optimal value of model parameters and objective

Table 3. The basic steps for PSO Algorithm

Algorithm 2	
Input	Set parameters: $\omega_{\min}, \omega_{\max}, c_1, c_2$
2	Initialize the population of each particle for positions *x* and velocities *v*
3	For each iteration (t), evaluate the fitness of particles
4	Find the index of the best particle P_{best} and G_{best}
5	Update velocity and position of each particle
6	$x_{ij}^{t+1} = x_{ij}^{t} + v_{ij}^{t+1}$
7	$v = w \times v_i^t + c_1 \times rand() \times (p_{best}^t - x_{ij}^t) + c_2 \times rand() \times (G_{best}^t - x_{ij}^t)$
8	Update $P_{best(t)}$ of population and $G_{best(t)}$
Output	Select the optimum solution as $G_{best(t)}$

5. Results and Discussions

First, the I-V and P-V curves for SDM are displayed in Figure (2) and Figure (3) for parameters that are evaluated using the PV module model design implemented in MATLAB

2018 software. The proposed method yielded five parameters, ideality factor, series resistance, and shunt resistance. To construct the module model, an actual PV module CS6P Canadian Solar was considered. The original PV module has 60 cells that must be connected in order to create the needed voltage. The parameters-based model selected from technologies used (Mono-crystalline and Polycrystalline modules) characteristics (Walker 2001)(Ibrahim and Anani 2017) under constant temperature and various circumstances of irradiance solar irradiation levels (200, 400,600, and 1000 W/m^2) to obtained and adjust I-V and power relationship characteristics of a PV module at various irradiance levels may be seen for the simulated model . Because of variations in solar power radiation throughout time, this is what happens. The tilt of the PV panel is critical for maximising power, and the numbers on the nameplate at the top of each panel are measured under standard test conditions in the manufacturing industry. When all other factors remain constant, that when the irradiance increases, the higher the output current, as shown in the figure 2, and as a consequence, the module is able to create more power as shown in Figure 3. However, iteratively altering the series resistance yields the same value of the maximum power within a small tolerance if the ideality factor is adjusted according to the kind of PV module, and the shunt resistance is calculated using the same method. The shunt resistan cell must have a big enough value to obtain the from the PV module. The standard output power for any model can be selected at standard solar radiation of 1000W/m2.

Then the PV modules are utilized and encoded into binary strings (chromosomes) to assist the convergence of PSO for the suggested approach. Tables 4 and 5 show the discovered parameters acquired by employing the suggested optimization approach.

Table 4. The I-V Model Parameters

Parameter	Value
N_{Cell}	54
I_{ph}	$1.00\times10^{-7}, 1.00\times10^{-6}$
I_{Sh}	6 A
Q	1.602e-19
G	1000
T_{n_d}	30+273 deg.cel
A	$0.5-2$ [1<A<2]
T_0	25 deg. cel
R_S	$50\Omega-200\Omega$
R_{sh}	0.22Ω
R_{Total}	$400\,\Omega$
V	36 v

Table 5. The PSO Parameters

Parameters	Values
Population size N	50
Acceleration coefficients c_1, c_2	2.0
Inertia weight $\omega_{min}, \omega_{max}$	0.4,0.9
Iterations	100

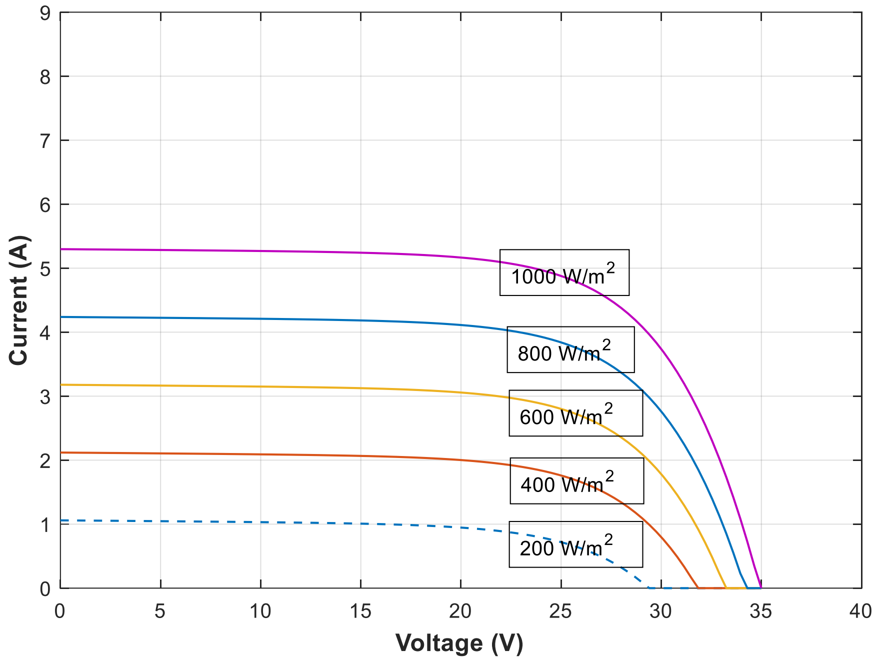

Figure 2. I-V curve of SDM under various irradiation settings and standard temperature.

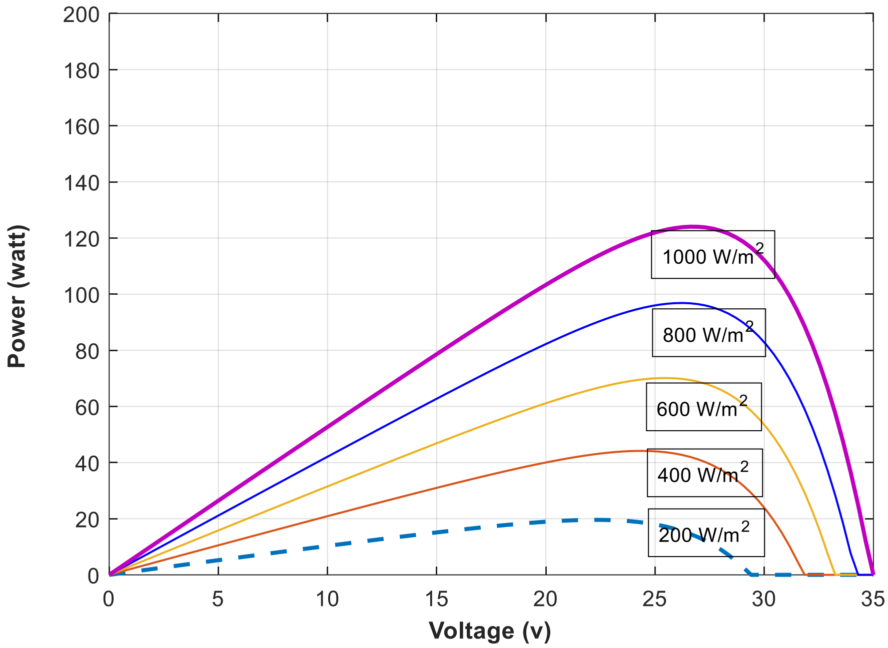

Figure 3. P-V curve of SDM under various irradiation settings and standard temperature.

Increasing the efficiency of the module is merely one method of obtaining additional energy from it. It is critical to know the solar power irradiance at which the PV model power calculations are performed during the actual computation of PV model power. While this is important, it is ultimately the system's overall energy output that counts most when it comes to improving PV efficiency at the system level.

5.1 PSO Algorithm Convergence Model

The performance of the proposed PSO approach optimization was examined. To fit the computed I-V curves for the two-diode model, the Particle Swarm Optimization approach described in Section 2.2 was used. The presents a process for selecting the best PV characteristics for the installation location. Decision-support systems incorporating multi-criteria analysis for PSO, are used to select the optimal installation site of the PVGCSs, taking into account environmental, location, topographic, and climate factors.

The PSO execution is influenced by characteristics of population size and acceleration coefficients. Figure (4) displays the proposed algorithm's optimum fitness value convergence. The optimization method has been repeated 100 times with different sizes of populations. for each sample of solution to check the variation in results. Using a random method, the PSO algorithm often yields an optimum solution after a few rounds. Further, to attain the average of optimum outcomes, the investigation of the convergence of PSO for the developed approach for PV modules is tested for each irritation varies value for constant temperature. The PSO was iterated 100 times with different populations to achieve optimal outcomes. Regardless of operation temperature and irritation value (W / m^2), the fitness value in curves converges to zero for all PV modules is equal. The fitness value decreases after every 100 generations, indicating algorithm converging. Therefore, the findings demonstrate the usefulness of the suggested approach in extracting the equivalent circuit model parameters with high precision.

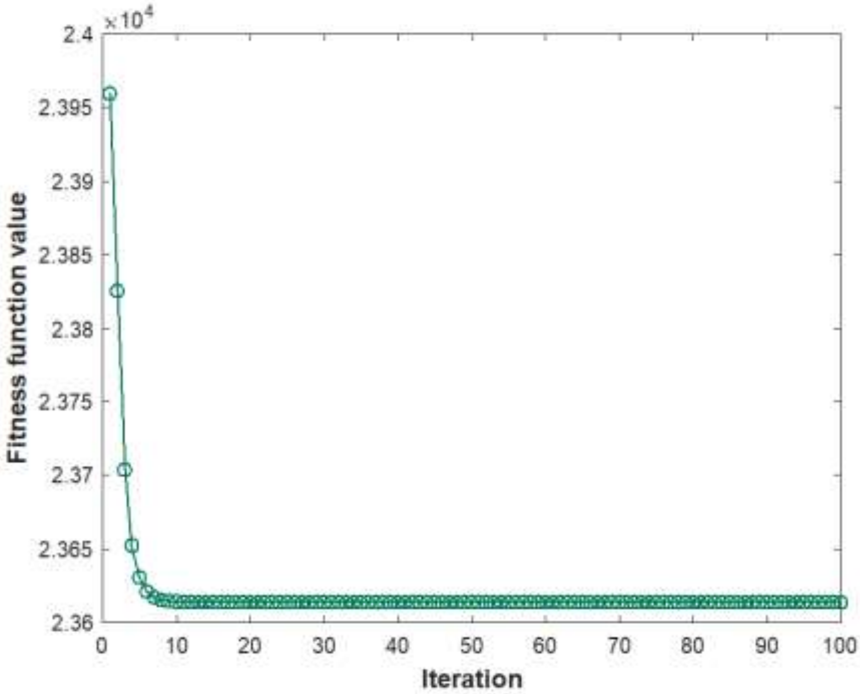

Figure 4. PSO Convergence Characteristic

6. Conclusion

This article provides an analysis of PV modeling and parameter extraction for numerous solar PV models. It reviews the notion of objective works, as well as the benefits and drawbacks of the various PV models, particularly the single diode and multi-diode models. The suggested technique's robustness has been demonstrated by testing three distinct PV modules. The proposed techniques are designed with the two innovative techniques as a point of reference. For both diode designs, the important parameter estimation is described and addressed for a solar PV model. Furthermore, the PSO algorithm is used to determine the parameters of a single diode model also aids in improving the overall performance efficiency and power extraction of the solar PV system.

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