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PSO-based Model and analysis of Photovoltaic Module Characteristics in Snowy Conditions

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Abstract: In this paper, a novel methodology of PV modeling is proposed to represent the instantaneous electrical characteristics of PV modules covered with snow. The attenuation of the transmitted solar radiation penetrating a layer of snow is rigorously estimated based on the Giddings and LaChapelle theory. This theory introduced the level of radiation that reaches the surface of PV module through snowpack, significantly affected by the snow properties and thickness. The proposed modeling approach is based on the single-diode-five-parameter equivalent circuit model. The parameters of the model are updated through instantaneous measurements of voltage and current that are optimized by the particle swarm optimization algorithm. The proposed approach for modeling snow-covered PV modules was successfully validated in outdoor tests using three different types of PV module technologies typically used in North America's PV farms under different cold weather conditions. In addition, the validity of the proposed model was investigated using real data obtained from the SCADA system of a 12-MW grid-connected PV farm. The proposed model can help improving PV performance under snow conditions and can be considered a powerful tool for the design and selection of PV modules subjected to snow accretion.

Nomenclature

R_s	series resistances in the PV module equivalent circuit	PSO	particle swarm optimization
R_{sh}	Shunt resistances in the PV module equivalent circuit	r_{ef}	effective grain radius
I_{ph}	photo-generated current	ψ	decision vector of PSO
I_s	Diode reverse saturation current	w	inertia weight
I_{sc}	Short circuit current of PV module	c_1, c_2	acceleration coefficients
α_0	diode ideality factor	r_1, r_2	random numbers
V_t	PV module thermal voltage	$x_i(j)$	Position of particles i in iteration number of j
N_s	Number of series connected cells in PV module	$v_i(j)$	Velocity of particles i in iteration number of j
T_c	panel temperature in Kelvin	$pbest_i(j)$	local best solution experienced by particle i in iteration number of j
k	Boltzmann's constant, $1.3806503 \times 10^{-23}$ J/K	$gbest(j)$	Global best solution of the entire swarm in iteration number of j
q	electron charge $1.60217646 \times 10^{-19}$ C	OF	objective function
$G_l(0)$	downward flux of radiation at snow surface	STC	standard test conditions
$G_l(x)$	downward flux of radiation at depth x	RMSE	root mean square error
α	albedo of snowpack		
ω	Reflection coefficient		
k_{ext}	extinction coefficient		
K_I	the temperature coefficient of short-circuit current		
K_V	the temperature coefficient of the open-circuit voltage		
K_{sf}	aging and dirt coefficient		
MPP	Maximum Power Point		
P_{max}	Peak power of PV module		
V_{mp}	voltage of PV module at the MPP		
I_{mp}	Current of PV module at the MPP		
ρ, ρ_i	densities of snow and ice respectively		

1. Introduction

1.1. Motivation and Incitement

In recent years, applications of PV technologies have offered promising solutions not only to fulfil the climate change target but also to reduce electricity generation costs. The maturity of solar photovoltaic (PV) technology is growing at an unprecedented rate. Solar systems are

becoming financially competitive because of the cost of solar electricity continues to decline [1]. As per the International Energy Agency (IEA) report, global electricity production from PV will grow to 953 TWh by 2025, which represents more than 400 % increase from 2014 [2]. The integration of PV systems into power grids has been also gaining popularity in climates with considerable snowfall. In 2009, nearly three-quarters of PV systems in the world were installed in countries such as Germany, Japan, Czech Republic and Canada that experience cold climate conditions [3]. For example, in Canada, the installed capacity of PV systems was around 1300 MW in 2013 with a growth of about 60% over the previous year. Moreover, estimates for the year 2020 predict an increase in the capacity of solar electricity to 6300 MW [4]. Snow accumulating on PV panels can reduce their energy production capability during cold months. In other words, layers of snow on the surface of PV panels can result in an inability of this costly technology to meet the power network requirements.

1.2. Literature Review

Over the years, several researchers have studied the effect of snow and ice on energy losses of PV systems. Investigations from the Natural Bridges National Monument, resulted in a daily loss prediction from 5% to 45% of system yield for two module angles of 30° and 40° depending on snow depth [5]. A study of PV losses due to snow shedding, performed in the Energy Diversification Research Laboratory, CANMET, analyzed the effect of temperature and melting technology in reduction of some losses [6]. Marion et al. concluded that snowfall could be a serious threat to the failure of grid-connected photovoltaic systems in Arizona, U.S. which can affect the overall system losses [7]. A six year-data acquisition of a 28 degree roof mount PV system in Germany showed that the values of proportional annual yield reduction by snowfall losses range from 0.3 to 2.7% [8]. The authors of [9, 10] introduced a generalized monthly snow loss model taking into account the effect of insolation, humidity, temperature, ground interference, and tilt angle for two PV sites in Truckee, CA, U.S. Average annual losses of 6% - 26% for different tilt angles of 35°-0° were obtained. Other reported measurements have also indicated that a PV system can have annual snow losses as high as 12% for a series of six PV systems in Colorado [11], 3.5% for a PV system of 70 PV modules in Ontario [3], and 5-12% for seven PV modules in four tilt angle assessed in Calumet, MI, USA [12]. In [13], a methodology that incorporates the Bouguer-Lambert Law [14] is proposed to estimate the transmitted level of insolation in deep layers of snow. However, it suffers from lack of accuracy to evaluate the diminished radiation intensity in light and medium snow coverage. Moreover, the parameters of the model for a particular environmental condition cannot be extracted simultaneously.

In most of the previous work reported in the literature, energy losses due to snow have been addressed and calculated through a simple comparison between expected energy and output measured power of PV systems based on offline models. However, research has not yet adequately addressed the challenges associated with the penetration of solar radiation through snow pack to the surface of PV

Fig. 1. Single-diode model of the ideal PV cell and equivalent circuit of a practical PV device including the series and parallel resistances.

modules. Thus, such models exhibit serious deficiencies for describing the various physical processes that have an impact on the conversion of photo energy into electricity. Consequently, they cannot be employed to characterize accurately the PV modules covered with snow. To cope with these shortcomings, an electric model of a PV sources in cold conditions could be a powerful tool not only for analyzing PV plant performance, but also for optimizing the power converter design and for studying the Maximum Power Point Tracking (MPPT) algorithms.

1.3. Contribution and Paper Organization

This paper proposes a PV model in which radiation intensity received on the PV surface is estimated based on the Giddings-LaChapelle theory [15]. Contrary to the Bouguer-Lambert Law, it enables an accurate estimation of the PV module behavior covered with thin and medium snow layers, particularly for critical snow depths less than two cm. Furthermore, the PSO algorithm, a powerful agent-based evolutionary algorithm (EA) is employed to determine and update instantaneous values of electrical model parameters of PV modules as per variable snow conditions. The proposed model offers a high accuracy in estimating electrical characteristics of snow-covered PV modules. The validity of the proposed approach was investigated against experimental measurements of three commercial PV modules covered with snow as well as those obtained from a 12-MW grid-connected PV farm. Moreover, a model that determines normalized PV system losses as a function of snow depth was proposed. Such a model can help PV developers design optimally PV farms in cold environments and take necessary measures for their maintenance, leading to an increase in an efficient lifetime.

The remainder of the paper is organized as follows. Section 2 describes the methodology proposed for the modeling of a snow-covered PV module. Section 3 discusses the proposed model validation. Finally, section 4 draws the conclusions of this paper.

2. Proposed Methodology for Creating Models of Snow-Covered PV Modules

Accurate modeling of I-V and P-V characteristics of a PV cell is required to emulate its behavior under various environmental conditions. The basic circuitry model of the ideal PV cell consists of a linear independent light generated current source connected in parallel with a single diode. In a real solar system, the electrical characteristics of the PV cell cannot be adequately modeled by an ideal PV cell equivalent circuit. The latter exhibits deficiencies in determining the performance of PV cells when subjected to climatic changes. Consideration of this issue leads to a

further extension of the previous model by the inclusion of additional shunt and series resistances. This can lead to an improved PV cell model with regard to the effect of temperature and insolation variation, particularly at low voltage [16]. The addition of extra diodes has been proposed to increase the accuracy of the model. However, this approach increases the model parameters and consequently the computational time. This is not efficient in online modeling of photovoltaic arrays [17]. To this end, the proposed methodology in this paper employs the single-diode equivalent circuit model as shown Fig. 1 [18]. From the theory of semiconductors, the implicit equation, which electrically represents the characteristics of the practical PV module in the output terminal, can be derived as:

$$I = I_{ph} - I_s \left[\exp \left(\frac{V + R_s I}{\alpha_0 V_t} \right) - 1 \right] - \frac{V + R_s I}{R_{sh}} \quad (1)$$

where R_s and R_{sh} represent the series and shunt resistances respectively, I_{ph} defines the photo-generated current by the incidence of light, I_s is the diode's reverse saturation current, α_0 is the diode ideality factor, and $V_t = N_s k T_c / q$ is the PV module thermal voltage.

2.1. The Penetration of Solar Radiation In Snow

To build an accurate model for the electrical performance of a snow-covered PV module, one should consider the influence of the penetration of solar radiation in the snow pack. Solar irradiation on the snow coverage is either absorbed by the refraction through some internal layer in the snow or is reflected and lost back into the atmosphere. Thus, the attenuation of incident light in snow is due both to the effects of extinction and of reflection. Albedo, which is defined as the ratio of the intensities of reflected radiation to incident radiation, is calculated using radiation intensities averaged over the short-wave radiation spectrum [3, 19]. On the other hand, the extinction of insolation through snow cover can be evaluated by choosing an average value for the extinction coefficient over the solar spectrum.

The albedo and the extinction of solar radiation in snow are coupled and strongly affected by the properties of the adjacent layer of snow on the surface [20, 21]. This coupling phenomenon was investigated through experiments conducted by Giddings and LaChapelle [15]. The penetration phenomenon is analyzed in terms of the physical processes occurred and formulated by the following equations that estimate the shortwave radiation penetration through an isotropic snow at depth x when a horizontal absorbing surface is placed at this depth beneath the laminated snow cover:

$$G_1(x) = \frac{G_1(0) \omega e^{-k_{ext} x} (1 + \tanh k_{ext} x)}{\left\{ 1 + \frac{\omega}{2} \left[1 + \frac{e^{-k_{ext} x} (1 - \frac{\omega}{2})}{\frac{\omega}{2} \cosh k_{ext} x + \sinh k_{ext} x} \right] \right\} (\frac{\omega}{2} + \tanh k_{ext} x)} \quad (2)$$

$$\alpha = \frac{1 - \frac{\omega}{2}}{1 + \frac{\omega}{2}} \quad (3)$$

where $G_1(0)$ and $G_1(x)$ represent the downward flux of radiation at snow surface and at depth x , respectively, α is the albedo of snowpack, ω is a dimensionless parameter which is related to reflection feature of snow. This important

optical property of snow can be empirically calculated as reflective indicator of light from snow accumulation on the surface and the surrounding snow-covered ground of PV panel and k_{ext} is the extinction coefficient which is represented by the physical properties of pertinent snow for evaluating the diminished isolation happened by the extinction phenomena through the snow layer.

Although the interpretation and direct measurement of incoming radiation flux within the snow is difficult, the albedo of a snow pack is a simpler, measureable and available parameter. The values of ω can be calculated by (3) according to measured values of albedo. Accordingly, for the albedo changes from 0.538 to 0.901, the value of ω varies in the range from 0.60 to 0.10 respectively [15]. In order to determine the extinction coefficient, the following equation that considers ice and snow conditions can be used [22].

$$k_{ext} = \frac{3\rho}{2\rho_i r_{ef}} \quad (4)$$

For different types of snow, from the soft new snow to the hard powder one, the value of extinction coefficient may range from around 10 m^{-1} to 55 m^{-1} ; for ice accumulation the values of k_{ext} range from 2 m^{-1} for clear ice to 20 m^{-1} for cloudy ice [6].

For a snow depth greater than a critical value of 2-4 cm, the Giddings-LaChapelle model can be merged with the Bouguer-Lambert Law to estimate the level of insolation that reaches the surface of PV cells covered with snow [14], such that:

$$G_1(x) = G_1(0) e^{-k_{ext} x} \quad (5)$$

It is important to recall that the Bouguer-Lambert Law exhibits low efficiency for low amounts of snow cover. Because, it only considers the extinction coefficient in its relationship. But by making use of the Giddings-LaChapelle theory, both extinction and reflection effects and their coupling are attended, one can estimate the insolation level reaching to the surface of PV cells for different range of snow thickness.

2.2. Determining The PV Module Parameters

In order to determine the current-voltage characteristic of a PV cell, it is required to compute five parameters i.e., I_{ph} , I_s , α_0 , R_s and R_{sh} , presented in equation (1). In majority of the cases, in order to simplify computations, the model incorporates only the variations of photo-generated current (I_{ph}) and diodes reverse saturation current (I_s), while the remaining parameters are kept constant. However, this simplification can negatively affect the accuracy of the model, particularly in snow conditions. Thus, the proposed approach presented in this work computes and updates simultaneously all the above-mentioned five parameters considering environmental conditions using the following steps:

Step 1: Photocurrent (I_{ph})

The photocurrent of a PV module covered by snow (I_{ph}) that depends on the intensity of incident insolation on the surface of the PV module and the module temperature can be obtained as [23]:

$$I_{ph} = \frac{G_{\downarrow}(x)}{G_{STC}} \cdot K_{sf} [I_{ph,STC} + K_I(\Delta T)] \quad (6)$$

where $I_{ph,STC}$ is the photocurrent of PV module in standard test conditions (STC) where the solar irradiance level has the value $G_{STC} = 1000 \text{ W/m}^2$, $\Delta T = T_c - T_{STC}$ is the temperature variation of the PV cells junction, $T_{STC} = 25 \text{ }^\circ\text{C}$, and the solar spectral distribution is equal to AM1.5 spectrum, K_{sf} defines the effect of aging and dirt in derating of PV module, and K_I is the temperature coefficient of short-circuit current reported by manufacturers.

Step 2: Diode reverse saturation current (I_s)

In the presence of snow at low irradiance levels, the open-circuit voltage of PV cell relevant to the variation of irradiance and temperature is calculated as follows [23]:

$$V_{oc} = V_{oc,STC} + V_t \ln(G_{\downarrow}(x) \cdot K_{sf} / G_{STC}) + K_V(\Delta T) \quad (7)$$

The values of $V_{oc,STC}$, the open-circuit voltage at STC, and K_V , the temperature coefficient of the open-circuit voltage, can be extracted from manufacturer datasheets. As a result, an improved equation which describes the saturation current I_s of the diode by considering both temperature and insolation is given by [24] and [25] as:

$$I_s = (I_{ph} - V_{oc}/R_{sh}) / (\exp(V_{oc}/\alpha_0 V_t) - 1) \quad (8)$$

Equations of voltage and current of PV module at the MPP can be developed as [24]:

$$V_{mp} = V_{mp,n} + V_t \ln\left(\frac{G_{\downarrow}(x)}{G_{STC}} \cdot K_{sf}\right) + K_{VP}(\Delta T) \quad (9)$$

$$I_{mp} = \frac{G_{\downarrow}(x)}{G_{STC}} \cdot K_{sf} [I_{mp,n} + K_{IP}(\Delta T)] \quad (10)$$

where $V_{mp,n}$ and $I_{mp,n}$ are the nominal voltage and current of MPP at STC and their correlate temperature coefficients K_{VP} and K_{IP} respectively, are taken from the manufacturer documents for the verities of PV modules.

Although the aforementioned equations represent the variations of photocurrent (I_{ph}) and diode saturation current (I_s) with respect to the temperature and irradiance in the presence of snow, their optimum values can be obtained by interaction with the remaining parameters (α_0 , R_s and R_{sh}) in different climatic conditions.

Step 3: Determination of α_0 , R_s and R_{sh}

The remaining parameters in (1), i.e. α_0 , R_{sh} and R_s are obtained through iteration process. Hence, initial guesses for R_s and R_{sh} are required. By substituting (9) and (10) in the following equation which represents the slope of the line segment between the short circuit and the maximum power remarkable points, the minimum values for the resistance can be determined [24].

$$R_s' = 0; \quad R_{sh}' = \frac{[V_{mp,n}/(I_{sc,STC} - I_{mp,n})]}{[(V_{oc,STC} - V_{mp,n})/I_{mp,n}]}, \quad (11)$$

The ideality factor of diode α_0 typically resides in a known range between $1 \leq \alpha_0 \leq 2$ [24]. In the above

equation, $I_{sc,STC}$ which is provided by manufacturer datasheets represents the short-circuit current under STC.

Step 4: Objective function

The optimization algorithm is applied to tune the values of parameters until the online experimental data are in accord with the I-V relation of (1). Therefore, (1) can be rewritten as below in order to construct a function that specifies the error between measured and calculated pairs of current and voltage values.

$$g(I, V, \psi) = I - I_{ph} + I_D + I_{Rsh} = \quad (12)$$

$$I - I_{ph} + I_s \left[\exp\left(\frac{V + R_s I}{\alpha_0 V_t}\right) - 1 \right] + \frac{V + R_s I}{R_{sh}}$$

where, $\psi = [R_{sh}, R_s, I_{ph}, I_s, \alpha_0]$ is the decision vector that includes the set of unknown parameters to be extracted accurately. In this work, the root mean square of the error function is employed as an objective function as follows:

$$OF = \sqrt{\frac{1}{N} \sum_{k=1}^N (g(I_k, V_k, \psi))^2}, \quad (13)$$

where I_k and V_k are the values of the k th pair of N data points in the experimentally measured I-V characteristics. Theoretically, the desired value for OF is zero if the exact values of each parameter have been found for any experimental I-V data. However, because of the noise of measurement and computation errors, it is expected to obtain a small value ($|\varepsilon| < 0.001$) for OF .

Step 5: Particle swarm optimization (PSO) algorithm

PSO is a stochastic optimization method, inspired by the behavior of a flock of birds or a school of fish, developed in 1995 [26]. In fact, the PSO as a metaheuristic approach is used to optimize a function that is difficult to express analytically. In PSO, the global position is searched by a number of agents (particles) with a continually updated velocity [27]. The movement of each particle around in the search space is controlled by its own best position and the globally best position found by all particles so far.

Each particle with the index of i emulates the success of neighboring particles and reaches its own success to find the best position (state) with time in a d -dimensional hyperspace. In each update with iteration index j , the current position $x_i(j+1)$ and velocity $v_i(j+1)$ of particles are dynamically adjusted regarding to their own previous best position experience $pbest_i(j)$ and the previous best solution $gbest(j)$ of the entire swarm as follows:

$$v_i(j+1) = \quad (14)$$

$$v_i(j) + c_1 r_1(j) \times [pbest_i(j) - x_i(j)] + c_2 r_2(j) \times [gbest(j) - x_i(j)],$$

$$x_i(j+1) = v_i(j+1) + x_i(j), \quad (15)$$

Fig. 2. The proposed PSO algorithm for PV modelling.

where w is the inertia weight, c_1 and c_2 are the acceleration coefficients, usually $c_1 = c_2 = 2$ and r_1 and r_2 are random numbers with values between 0 and 1. Possible solution of optimization problem is represented by the position of each particle that corresponds to the set of solar cell parameter values. The global search and local search of a solution can be ideally balanced by using a value of selected inertia weight as follows:

$$w(j) = w_{max} - (w_{max} - w_{min}) \frac{j}{j_{max}}, \quad (16)$$

In this equation, j_{max} indicates the maximum iteration times (generation size). Improved convergence speed was observed by the variation of inertial weight from $w_{max} = 0.9$ to $w_{min} = 0.4$ over entire search range. It also avoids premature convergence, and reduces the total number of iterations [28].

The changes of velocity vector of each particle in (14) can be further updated by the following law:

$$v_i(j+1) = \begin{cases} V_{max}, & \text{if } v_i(j+1) > V_{max} \\ -V_{max}, & \text{if } v_i(j+1) < -V_{max} \\ v_i(j+1), & \text{otherwise,} \end{cases} \quad (17)$$

In the above relation, V_{max} represents the maximum permitted excursion of any particle in that dimension to clamp the unnecessary movement of particles [26].

Personal best position of each particle can be updated by comparing the personal best of each particle to its current fitness, and set to the better performance according to the following relation.

$$pbest_i(j) = \begin{cases} pbest_i(j-1), & \text{if } OF(x_i(j)) \geq OF(pbest_i(j-1)) \\ x_i(j), & \text{if } OF(x_i(j)) < OF(pbest_i(j-1)) \end{cases} \quad (18)$$

The position of the particle with the best fitness within the entire swarm sets the global best as follows:

$$gbest(j) \in \{pbest_1(j), pbest_2(j), \dots, pbest_{N_s}(j)\} | OF(gbest(j)) = \min \{OF(pbest_1(j)), OF(pbest_2(j)), \dots, OF(pbest_{N_s}(j))\}, \quad (19)$$

Fig. 2 depicts the flow chart of the proposed method in conjunction with the PSO algorithm.

The proposed PSO method enables simultaneous computation of unknown values of α_0 , R_s and R_{sh} and optimal values of I_{ph} and I_s with respect to the temperature and irradiance in the presence of snow. The values of optimized extracted parameters, their relevant minimum objective functions, time of calculation and the bound of search range are illustrated in table 1.

If the population size and iteration times define too small, it leads to the poor results because of the limitation of space for exploring the solution. As consequence in the following experiments for operating the modeling algorithm, control variables of PSO have been executed by defining the 100 number of particles and 10000 as the maximum iteration times. The objective (fitness) function specified as the root mean square error between measured and calculated pair of voltage and current data point vary from 135 to 200 points in different type of panels.

Fig. 3. Experimental set-up for the snow covered PV modules.

TABLE 1 optimized parameters of the PV modules extracted by the proposed algorithm

Parameters	CS6P-260P				ET-M53695				FS 275			
	Range	1	2	3	Range	1	2	3	Range	1	2	3
$I_{ph}(A)$	[0,10.14]	5.0763	3.194	0.9823	[0,7.34]	3.719	1.3204	0.27923	[0,1.66]	0.84057	0.61658	0.28483
$I_s(A)$	[0, 3.5 × 10 ⁻⁸]	2.617 × 10 ⁻¹¹	1.6464 × 10 ⁻¹¹	5.0589 × 10 ⁻¹²	[0, 6.6 × 10 ⁻⁹]	5.1609 × 10 ⁻¹¹	1.8179 × 10 ⁻¹¹	3.5855 × 10 ⁻¹²	[0, 1.6 × 10 ⁻¹¹]	1.9551 × 10 ⁻¹⁴	1.4434 × 10 ⁻¹⁴	6.5289 × 10 ⁻¹⁵
α_0	[1,2]	1.0027	1.0052	1.0085	[1,2]	1.0504	1.0519	1.0532	[1,2]	1.0165	1.0069	1.0133
$R_{sh}(\Omega)$	[53,3000]	501.023	782.4833	2348.1286	[41,3000]	112.493	560.0398	1223.696	[505,5000]	1411.8196	2230.4348	3128.2938
$R_s(\Omega)$	[0,10]	0.61808	0.98531	3.2224	[0,10]	0.39453	1.1064	5.3276	[0,100]	17.9777	24.0628	53.9588
Time (s)		275	317	243		205	215	328		289	241	314
OF _{min}		4.21 × 10 ⁻⁴	4.01 × 10 ⁻⁴	3.97 × 10 ⁻⁴		4.56 × 10 ⁻⁴	4.89 × 10 ⁻⁴	4.78 × 10 ⁻⁴		4.73 × 10 ⁻⁴	4.69 × 10 ⁻⁴	5.03 × 10 ⁻⁴

Fig. 4. I-V and P-V curves obtained using the proposed model and experimental data under various climate conditions and for different snow depths for: (a) CS6P-260P (polycrystalline), (b) ET-M53695 (monocrystalline), and (c) FS-275 (thin film).

In the optimization problem based on PSO for extracting solar cell parameters, the fitness function and the objective function are identically described as (13). The smaller the objective function, the better the fitness of an individual. Furthermore, reaching to the maximum iteration number j_{max} or satisfying the minimum fitness function OF_{min} are used as the stopping criteria in this case.

3. Model Evaluation

The accuracy of the proposed method in determining I-V and P-V characteristics is validated using experimental data of uniformly snow-covered PV modules of different technologies and also using real data acquired using the SCADA system of a grid-connected PV farm.

3.1. Test Bed Design and Installation

A series of experiments were carried out using three different types of PV module technologies i.e., an ET-M53695 monocrystalline PV module from ET Solar manufacturer, a CS6P-260P polycrystalline PV module from Canadian Solar manufacturer, and a FS-275 thin film PV module from First Solar manufacturer to measure electric characteristics of PV module. The parameters of the test bed panels are provided in table 2. A comparison between the measured short-circuits current of the PV panels and the ones provided by the manufacturers datasheet was performed to obtain the value of K_{sf} , used in (6). This coefficient was found to be approximately equal to 1 for the CS6P-260P and FS-275 PV panels as new technologies, while it was determined to equal 0.97 for the ET-M53695 panel.

As shown in Fig. 3, the PV modules with snow coverage were faced due south with a tilt angle of 30° under the test condition. The test bed was racked with the latitude of 45.47° . Data acquisition was conducted using HT Instruments I-V 400 PV Panel Analyzer and irradiance meter test kit to export the PV characteristics. The quick and

reliable temperature measurement of the back surface of modules was carried out by a Fluke 62 Mini infrared thermometer. An electronic digital caliper was employed to measure the snow depth. Snow densities were determined using a digital scale. A magnifying glass and a millimeter-scale grid were used to acquire the size of snow grains. For different snow patterns over the experiments, the extinction coefficient ranged between 18 m^{-1} and 54 m^{-1} .

TABLE 2 electrical parameters of the test bed solar panels

Parameters	CS6P-260P	ET-M53695	FS 275
P_{max} (W)	260	95	75
V_{mp} (V)	30.4	18.52	68.2
I_{mp} (A)	8.56	5.13	1.10
V_{oc} (V)	37.5	22.5	89.6
I_{sc} (A)	9.12	5.57	1.23
N_s	60	36	116

3.2. Results validation and discussion

The I-V and P-V characteristics of the simulated model are compared with those measured from the test field to experimentally validate the effectiveness of the proposed PV model approach as shown in Fig. 4. The circle markers in blue represent the experimental measurements, while the modeled results are marked by the red solid lines. A good concordance was identified between the simulated current values obtained by employing the model and the experimental ones. Since the field information, physical characteristics of the snow coverage, including density, depth, and an estimation of grain size as well as manufacturer data are taken into account, the proposed model has the capability to reflect the impact of variable weather conditions on the behavior of PV modules.

Fig. 5 shows the convergence performance, a fitness index between experimental data and those calculated by the proposed PSO-based PV model for the three different PV technologies as per the objective function of (13). Fig. 5 highlights the ability of the model to determine the PV curve

Fig. 5. Root mean square error between the proposed model and the experimental data.

characteristics with a root mean square error (RMSE) of 0.0004. It exhibits very high fitness value OF that offers very high accuracy.

3.3. Snow-Related Power Loss

The performance of PV modules can be negatively affected by snowfall during cold months. In fact, snow accretion can cause obstacles on the PV module surface to receive maximum irradiance, consequently leading to a reduction in energy production. In order to evaluate the impact of snow on the performance of PV modules, a series of measurements of the CS6P-260P polycrystalline PV module under different snow depth were carried out and the MPP values of P-V curves was recorded. A comparison between the expected MPPs of the snow-free PV module and those obtained from snow-covered one, as shown in Fig. 6, highlights a significant reduction in the output power with an increase in the snow depth. In order to normalize power losses due to snow, the percentage of loss, obtained by comparing the MPPs of the snow-covered PV modules with those obtained for clean modules, is also shown in Fig. 6. It can be observed from Fig. 6 that a PV module can experience power losses more than 50% when the snow depth reaches the critical depth of 2 cm.

The percentage of loss in the power generation of PV modules as a function of snow depth, average amount of extinction coefficient k_{ext} and ω can be expressed by (20). The dashed line in green in Fig. 6 illustrates the amount of the estimated power loss by considering average values of 35.5 m⁻¹ and 0.315 for the extinction coefficient and ω respectively. The proposed power loss equation can offer a good tool to select PV modules for locations exposed to freezing conditions. Contrary to the power loss model proposed in [13], the proposed Giddings and LaChapelle - based power loss model shows a higher accuracy in predicting the energy efficiency. This is due to the fact that Giddings and LaChapelle approach shows better performance under light and medium snow accretion in comparison with the Bouger-Lambert Law.

$$P_{loss}(\%) = \left[1 - \omega e^{-k_{ext}x} (1 + \tanh k_{ext}x) / \left\{ 1 + \frac{\omega}{2} \left[1 + \frac{e^{-k_{ext}x} (1 - \frac{\omega}{2})}{\cosh k_{ext}x + \sinh k_{ext}x} \right] \right\} \left(\frac{\omega}{2} + \tanh k_{ext}x \right) \right] \times 100 \quad (20)$$

3.4. Industrial Case

Fig. 6. Effect of different snow depths on power production and loss of CS6P-260P.

The great merit of the proposed PV modeling method can be accentuated by calculating power losses of a 12-MW grid-connected PV farm. The data we used comes from a farm that is located in Ontario, Canada. This location consists of the south-facing thin film PV panels with a fixed tilt-angle. Hourly-average data acquisition of the PV farm such as the back-surface temperature and the tilted irradiance of PV panels, along with the module DC voltage, DC current and the AC power of the inverters is recorded by the SCADA system of the PV farm. The maximum power of the PV arrays is extracted by assigning an MPPT control for the grid-connected inverters in PV farms. Data of the SCADA system such as the snow properties and its depth as well as the irradiance and temperature were acquired when PV modules were covered with snow for two typical days of December 2015 and January 2016 after the precipitation.

Table 3 indicates the energy generation of the 12-MW PV farm for these two mentioned days based on the novel approach proposed in this paper and the previous model presented in [13] for the same case study. It can be seen that a higher level of accuracy is achieved in compare with the previous model since the proposed approach uses the Giddings and LaChapelle law that shows high efficiency in determining receiving solar radiation on the PV module surface.

TABLE 3 Energy generation of a 12-MW PV Farm for Two Typical Days

	Day 1 (h=1.6 cm)	Day 2 (h=2.55 cm)
SCADA database	46.234 MWh	29.418 MWh
Proposed model	47.58 MWh	30.48 MWh
Error of proposed model	2.92 %	3.6 %
Error of reference [13]	6.3 %	6.8 %

4. Conclusion

A PSO-based PV model was proposed to predict the behavior of snow-covered PV modules. It capitalizes on the Giddings and LaChapelle theory to determine accurate solar receiving solar radiation on the PV module surface and the PSO algorithm to update PV module parameters under different snowfalls. The model was validated experimentally using PV modules based on different technologies, as well as using real data from a 12-MW PV farm. The results obtained by the proposed model are in a good agreement with those obtained experimentally. The model offers thus a

great advantage in predicting electric characteristics of PV modules under different snow conditions, from light to heavy snowfall because the albedo and the extinction of solar radiation are coupled based on the Giddings and LaChapelle theory. The results obtained are of great importance as they can help to improve the electrical performance of PV systems under snow conditions. In this work, the most probable factors in the presence of snow have been considered to emulate a realistic situation of PV systems in compare with previous studies. Hence, there is some open problems with lower probability like non-uniformity of snow layer or partial shading of panel surface can be investigated for the future works.

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6. References

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