

Research Article

Metaheuristic Optimization of Fractional Order Incremental Conductance (FO-INC) Maximum Power Point Tracking (MPPT)

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This paper seeks to improve the photovoltaic (PV) system efficiency using metaheuristic, optimized fractional order incremental conductance (FO-INC) control. The proposed FO-INC controls the output voltage of the PV arrays to obtain maximum power point tracking (MPPT). Due to its simplicity and efficiency, the incremental conductance MPPT (INC-MPPT) is one of the most popular algorithms used in the PV scheme. However, owing to the nonlinearity and fractional order (FO) nature of both PV and DC-DC converters, the conventional INC algorithm provides a trade-off between monitoring velocity and tracking precision. Fractional calculus is used to provide an enhanced dynamical model of the PV system to describe nonlinear characteristics. Moreover, three metaheuristic optimization techniques are applied; Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO), and AntLion Optimizer (ALO) are used for tuning the FO parameters of the proposed INC-MPPT. A MATLAB-Simulink-based model of the PV and optimization have been developed and simulated for different INC-MPPT techniques. Different techniques aim to control the boost DC-DC converter towards the MPP. The proposed optimization algorithms are, also, developed and implemented in MATLAB to tune the target parameters. Four performance indices are also introduced in this research to show the reliability of the comparative analysis of the proposed FO-INC with metaheuristic optimization and the conventional INC-MPPT algorithms when applied to a dynamical PV system under rapidly changing weather conditions. The simulation results show the effective performance of the proposed metaheuristic optimized FO-INC as a MPPT control for different climatic conditions with disturbance rejection and robustness analysis.

1. Introduction

Green energy sources are the primary research goal nowadays as they are viable, ecological, and cost-effective energy sources. Solar, wind, tidal, and biomass energy have penetrated the electric power production market in recent years due to the diverse methods and their renewable nature. The benefits of developing renewable power include reducing fossil fuel usage, mitigating the greenhouse impact, and reducing air pollution [1]. In addition, control approaches and optimization have shown that the performance of photovoltaic devices depends upon climate

conditions (sunlight and temperature) and load impedance [2]. However, its low energy conversion effectiveness (especially in low radiation and temperatures) is the primary disadvantage of PV systems. The MPPT needs to be operated for ideal efficiency and operation as mentioned [3]. One of the pioneering challenges of the PV devices is their nonlinear current-voltage I-V relationship dynamic which generates a distinctive MPP in the power-voltage P-V relationship as noted [4]. Because of the P-V relationship with climate and load circumstances, the MPPT method becomes complex. MPPT methods do not only enhance the power performance of PV and energy

delivered to the load, but they also increase the operating life of the PV system [5]. Previous studies have suggested several MPPT methods; most MPPT techniques demonstrate higher efficiency under stable weather [6]. MPPT algorithms are usually used as electronic power conversion devices and the control signal is a duty cycle for peak load energy [7]. A wide variety of methods for solving the MPPT issue have been implemented, such as the perturb and observe (P&O) method, incremental conductance (INC) algorithm, and artificial intelligence includes fuzzy logic, neural networks, and metaheuristic techniques. The P&O and INC are the most common algorithms used for PV-MPPT systems [8]. The P&O technique is frugal and very easy to execute; its operation is based on the iterative measurement of the voltage and current of the PV system to obtain the duty cycle and consequently the MPP. Its main disadvantage, however, is that it provides an oscillatory power around the MPP and is also unable to manipulate PV power variations due to climatic effects or inherent disturbances of the MPPT. The INC approach is based on the behavior of PV, given that a MPP is reached by zero in a pitch of the PV curve, positive to the left and negative to the right of the PV curve. On the basis of this, the technique calculates the DC-DC converter duty cycle by relating iterative conductivity to the incremental conductivity. The primary drawback in the INC technique is that the system's reaction to the MPP may be slow under some conditions. However, the INC technique exhibits less oscillatory behavior around the MPP compared to the P&O method [9]. Fractional calculus introduces the nonintegral order/fractional of derivatives and integrals. Many of the real systems show a nonlinear and fractional order dynamical behavior, such as heat conduction in solids, electrical behavior in R-L transportation lines, mass diffusion, and electromagnetic waves [10]. The nonlinear characteristics of the current-voltage of a PV cell occur because the PV cells are manufactured from semiconducting materials (crystalline silicon, c-Si). The power of PV cell depends on the inherent voltage drop across the p-n junction (energy band) which produces a photoelectric current (current source). The light and ambient temperature interaction also shows anomalous diffusion which can be described as fractional order diffusion [11]. Therefore, Grunwald-Letnikov fractional approximation [12] is introduced to control the fractional order differentiation for current and voltage nonlinear dynamical behavior. To improve dynamic performance, FO-INC based on the nonlinear and fractional order changes of the PV voltage and current has been proposed to track the maximum output power [13]. It is very important to select the proper converter [14] to enhance the MPPT performance. The MPPT techniques have been compared using MATLAB and Simulink tools created by MathWorks, considering all the design and implementation specs [15]. Therefore, metaheuristic optimization techniques' robustness and ability to find the optimal solution in different nonlinear systems have demonstrated itself in numerous past research studies. Metaheuristic abilities are powerful techniques of resolving optimization problems for nonlinear and fractional order

systems [15]. In power systems, different optimization techniques have been utilized. Considering the different constraints in PV systems and difference in the nature of DC-DC converter system, the ACO algorithm has been used [16]. It has been proved to be very robust, consistent, and performs better than conventional optimization techniques (e.g., PSO and GA) [16]. The experiments show computational effectiveness and time decrease in monitoring for a small PV Systems. The AntLion optimizer (ALO) is a recent metaheuristic algorithm that replicates the hunting scheme of antlions in catching ants [17]. ALO also gives a good performance results in PV-MPPT systems [18]. This research aims to extract maximum power from PV systems by using FO-INC and metaheuristic optimization technique. This enhanced system efficiency in different climatic conditions using fixed and variable-step FO-INC with PSO, ACO, and ALO optimization techniques. This paper is organized as follows: Section 2 addresses the modeling of the complete PV system, and Section 3 describes the MPPT algorithm design and operation. Section 4 gives the operation of metaheuristic optimization algorithms. Sections 5 and 6 illustrate the experimental results and conclusions to show the efficiency of the proposed technique.

2. Photovoltaic (PV) System Modeling and Simulation

The proposed PV system is constituted by a PV module, the Buck-Boost converter as a DC-DC converter between the PV panel and the DC load, and the MPPT controller to achieve maximum power point of the PV panels. The model of the solar panels used in the proposed system will be illustrated, and the PV system is introduced [19]. The inputs to MPPT are the PV voltage and current which are used to calculate and deliver the control signal (duty cycle) to the Buck-Boost converter, as shown in Figure 1. The main function of the MPPT algorithm is to automatically track the voltage/current change of the PV panel and feed the Buck-Boost converter with the appropriate duty cycle to get the MPP under specific climatic conditions.

2.1. Modeling of PV Panel. The nonlinear equations of the PV system which describe the relationships between the different PV model parameters are developed and solved via MATLAB and Simulink tools where the PV cell electric circuit model is shown in Figure 2. The PV output current I_{PV} can be obtained using equation (1) where N_p and N_s are the number of parallel and series cells, respectively:

$$I_{PV} = N_p \times (I_G - I_D - I_{sh}). \quad (1)$$

The nonlinear equation of I-V characteristics of one-diode PV model was expressed by Milici et al. [9] as follows:

$$I_{PV} = N_p \times I_G - N_s \times I_o \left[e^{((q/nkT_k) \times ((V_{PV}/N_s) + (I_{PV}/N_p)R_s) - 1)} \right] - \frac{N_p}{R_{sh}} \times \left(\frac{V_{PV}}{N_s} + \frac{I_{PV}R_s}{N_p} \right), \quad (2)$$

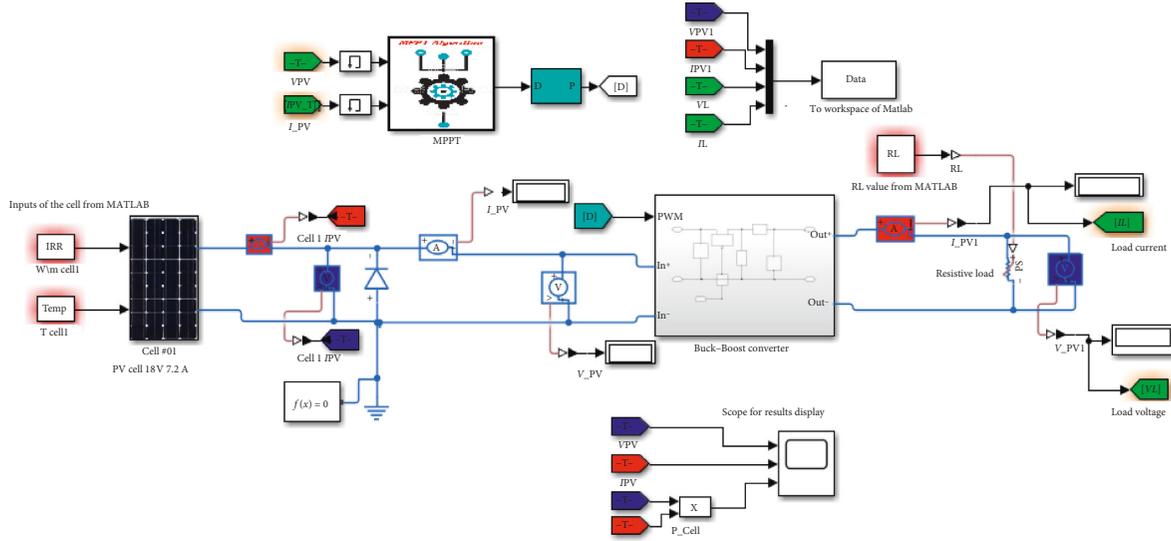


FIGURE 1: Complete PV system model using MATLAB and Simscape.

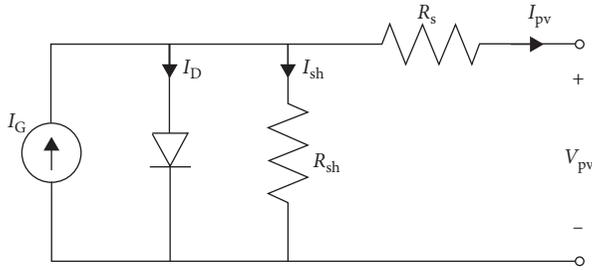


FIGURE 2: PV cell equivalent electric circuit model.

where V_{PV} and I_{PV} are the PV terminal voltage and current, respectively, R_s and R_{sh} are the series and shunt resistance, respectively, η is the ideality factor, the Boltzmann's constant is k , q is the electron charge, T_k is the temperature degree in Kelvin, I_G is photo-generated current, and the diode saturation current is I_o . The PV panel parameters are shown in Table 1.

The I-V and P-V nonlinear characteristic curves of the PV array simulated using MATLAB at different climatic conditions (temperature and irradiance) are shown in Figure 3.

2.2. DC-DC Converter. Simulink and Simscape tools have been selected as platforms for modeling, implementation, and testing the Buck-Boost converter. The state space modeling is primarily represented by equation (3), where A , B , C , and D are the system matrices, x is the state variable vector, x' is the state variable derivative vector with respect to time, u is the input, and y is the output [14]:

$$\begin{aligned} x' &= Ax + Bu, \\ y &= Cx + Du. \end{aligned} \quad (3)$$

Figure 4 shows the Buck-Boost model using Simscape which is simulated at different duty cycles and fixed load

TABLE 1: PV panel parameters.

Parameter value	Value
Max power P_{max}	735.72 W
Open circuit voltage V_{oc}	65.9 V
Short circuit current I_{sh}	15.21 A
Temperature coefficient of V_{OC}	-1.23×10^{-1} V/C
Temperature coefficient of I_{sh}	3.18×10^{-3} A/C

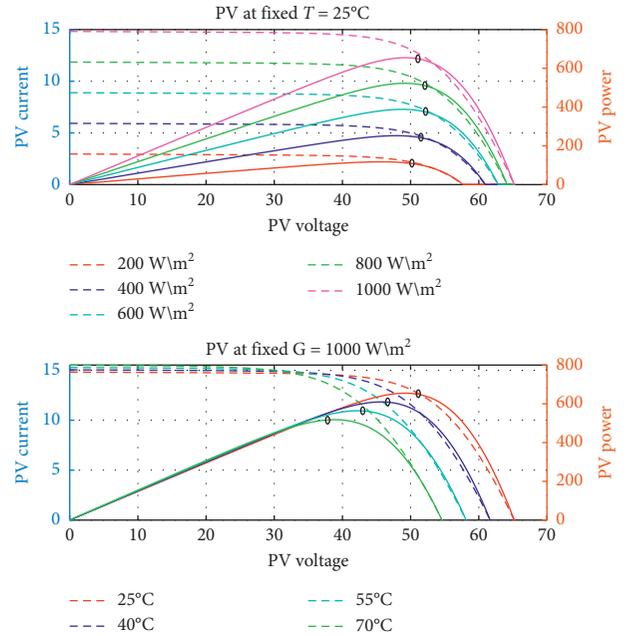


FIGURE 3: P-V and I-V characteristic curves at different climatic conditions.

according to the state space model represented in equation (4), where $x_1 = I_L$, $x_2 = V_{C_{out}}$, and $d =$ duty cycle. The simulation results at different duty cycles are shown in Figure 5:

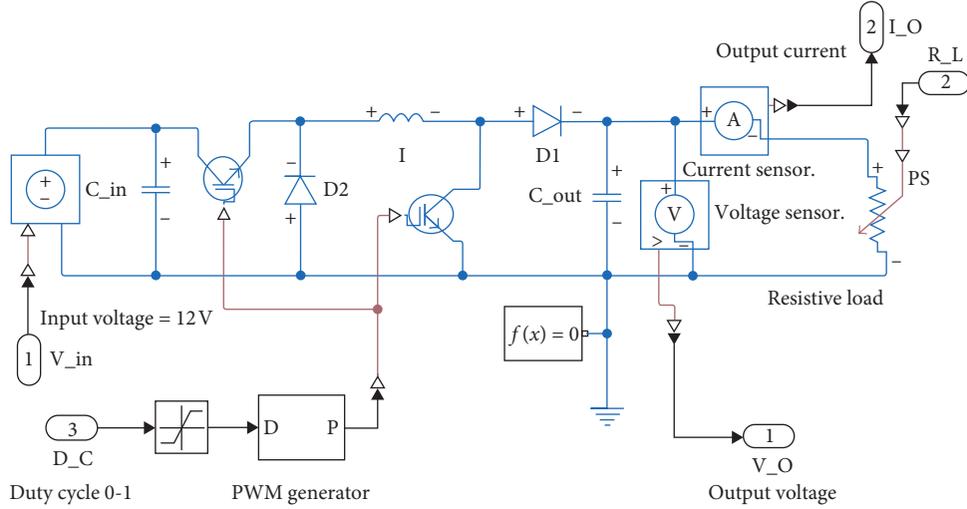


FIGURE 4: Buck-Boost Simscape model.

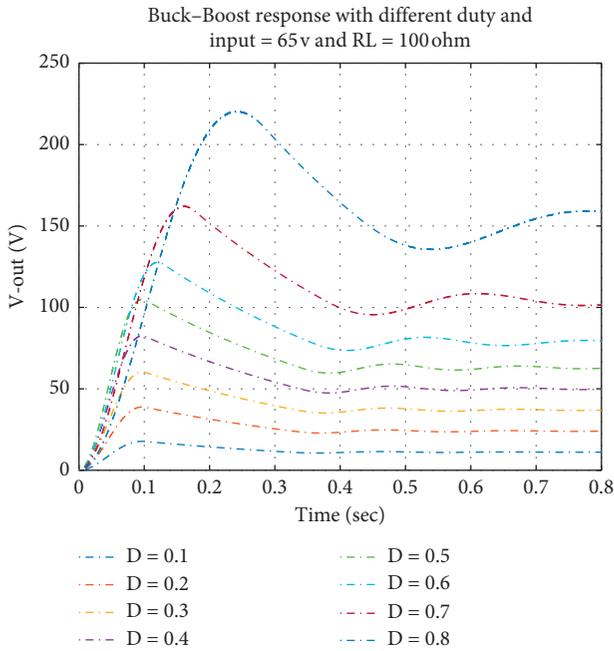


FIGURE 5: Buck-Boost output voltage at different duty cycles.

$$\begin{bmatrix} x_1' \\ x_2' \end{bmatrix} = \begin{bmatrix} 0 & \frac{1-d}{L} \\ -\frac{(1-d)}{C} & -\frac{1}{RC} \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} + \begin{bmatrix} \frac{d}{L} \\ 0 \end{bmatrix} u_1, \quad (4)$$

$$\begin{bmatrix} y_1 \\ y_2 \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} I_L \\ V_{C_{out}} \end{bmatrix} + \begin{bmatrix} 0 \\ 0 \end{bmatrix} u_1.$$

The proposed Buck-Boost has been designed and simulated using the parameters illustrated in Table 2.

TABLE 2: Buck-Boost design parameters.

Parameter value	Value
Load resistance	4.5 Ω
Filter inductance	1 mH
Output filter capacitance	4700 μ F
Input filter capacitance	47 μ F
Switching frequency	25000 Hz

3. Design and Implementation of MPPT

The primary feature of the PV system is the total energy monitoring in which the power of the PV modules can be extracted in a certain climatic situation. As shown in the literature, the most commonly used MPPT algorithm is INC. The INC algorithm is based on the reality that the PV output energy derivative for the output voltage at the MPP is zero ($dP/dV = 0$), positive on the left side of MPP ($dP/dV > 0$) and negative on the right side of MPP ($dP/dV < 0$) [5].

3.1. Fixed-step INC Method. The INC algorithm is used to detect the condition of MPP via the conductance (dI/dV) behavior of the PV system. The INC-MPPT can be executed through the following sequence [20]:

- (1) The voltage and current of the PV module are sensed by the MPPT controller
- (2) If ($dI/dV < -I/V$) is satisfied, the duty cycle of the converter needs to be decreased and vice versa
- (3) No change in the duty cycle occurs if $I + V(dI/dV) = 0$ is satisfied

The duty cycle (PV reference voltage (V_{ref})) increasing or decreasing occurs with fixed step.

3.2. Variable-Step INC Method. The INC variable step size algorithm proposed by Motahhir et al. [5] can improve the MPPT controller's tracking effectiveness. The algorithm

sequences are mostly comparable to the standard increments; the only distinction is the calculation of the step size. $\text{Step} = N * \text{abs}(dP/dV)$ is used in the variable step size algorithm to change the duty cycle step size, where N is the scaling factor.

3.3. Fractional Order INC Method (FO-INC). Many computational requests for fractional order derivatives according to the definition have been suggested by Riemann–Liouville and Grunwald–Letnikov, [9]. The general form of fractional order differentiator can be expressed by Kamal and Ibrahim [21]; supposed that $f_m(t) = t^m$ and $m = 1, 2, 3, \dots$, is demonstrated at

$$D_{\alpha}^t t^m \approx \frac{\Gamma(m+1)}{\Gamma((m+1)-\alpha)} t^{(m-\alpha)}, \quad (5)$$

where $\Gamma(\cdot)$ represents Euler's gamma function and α is the order number of derivative, when its value is $0 < \alpha < 1$, representing physical phenomenon of fractional order [9]. The FO-INC MPPT main criteria can be expressed by equations (7) and (8):

$$\frac{d^{\alpha} I(V)}{dV^{\alpha}} = \lim_{\Delta V \rightarrow 0} \frac{I(V) - \alpha(V - \Delta V)}{\Delta V^{\alpha}}, \quad (6)$$

$$\frac{d^{\alpha} I}{dV^{\alpha}} \approx \frac{I - \alpha I_0}{(V - V_0)^{\alpha}}, \quad (7)$$

$$\frac{d^{\alpha}}{dV^{\alpha}} \left(\frac{-I_0}{V_0} \right) = \left(\frac{-1}{V} \right) \left(\frac{\Gamma(2)}{\Gamma(2-\alpha)} \right) (I_0)^{1-\alpha} - I_0 \frac{\Gamma(0)}{\Gamma(-\alpha)} V_0^{1-\alpha}. \quad (8)$$

The control procedure of the FO-INC algorithm can be expressed by the flowchart depicted in Figure 6. The procedure starts with measuring the PV's voltage and current to determine the MPPT action according to the following conditions:

Condition 1. If $(\Delta V^{\alpha} \neq 0 \& (d^{\alpha} I/dV^{\alpha}) = (d^{\alpha}/dV^{\alpha}) (-I_0/V_0))$ or $(\Delta V^{\alpha} = 0 \& \Delta I = 0)$, keep the current duty cycle, fix the duty cycle

Condition 2. If $(\Delta V^{\alpha} \neq 0 \& (d^{\alpha} I/dV^{\alpha}) > (d^{\alpha}/dV^{\alpha}) (-I_0/V_0))$ or $(\Delta V^{\alpha} = 0 \& \Delta I > 0)$, decrease the duty cycle of the Buck–Boost converter (increase V_{ref} as in equation (9))

Condition 3. If $(\Delta V^{\alpha} \neq 0 \& (d^{\alpha} I/dV^{\alpha}) < (d^{\alpha}/dV^{\alpha}) (-I_0/V_0))$ or $(\Delta V^{\alpha} = 0 \& \Delta I < 0)$, increase the duty cycle of the Buck–Boost converter (decrease V_{ref} as in equation (9))

Condition 4. Calculate $P_o = V_o \times I_o$ and $P = V \times I$. If $P > P_o \rightarrow$ terminate, otherwise update the voltage $V_o = V$, current $I_o = I$, and power $P_o = P$

The duty cycle of the Buck–Boost converter can be calculated based on the output of the FO-INC controller V_{ref} as in

$$V_L = \frac{D}{1-D} \times V_{\text{PV}} \text{ then,} \quad (9)$$

$$D = \frac{V_L}{(V_0 \pm \Delta V^{\alpha}) + V_L},$$

where V_L is the resistive load voltage, $V_{\text{PV}} = V_{\text{ref}}$, and D is the duty cycle.

Both fixed- and variable-step FO-INC MPPT have been implemented to improve the performance of the MPP tracking of the nonlinear PV system with Buck–Boost converter and resistive load. In case of fixed step, the effective parameter of MPPT performance is alpha α . For variable step both alpha (α) and step size S are affecting the MPPT performance as shown in Figure 6.

4. Metaheuristic Optimization Algorithms

Genetic algorithms, Particle Swarm Optimization, and Ant Colony Optimization are among the most frequent algorithms in this field. However, these algorithms can solve many real and difficult problems. As one of the recent algorithms, the AntLion Optimizer Optimizer will be introduced along with its basic working principle, updated criteria, and pseudo algorithms. According to Pradhan et al. [20], the searching techniques of different optimizers are as follows:

- (1) Initialize solution randomly
- (2) Specify the search direction
- (3) Specify the update criteria
- (4) Specify the stopping criteria

4.1. Particle Swarm Optimization (PSO). The inspiration of the particle swarm algorithm is to simulate the navigation and foraging of swarm of birds or school of fishes. PSO was developed by James Kennedy and Russel Eberhart in 1995 while studying the social behaviors of animals working in swarms [22]. The PSO is seeking high-quality optimization by refining, iteratively, a candidate solution. The pseudo code of the PSO algorithm is illustrated in detail with the steps in Algorithm 1. In Algorithm 1, N is the number of particles, C_1 and C_2 are the acceleration coefficients, and W_{min} and W_{max} are the ranges of weight of particles. PSO uses fewer resources than the other optimization techniques. Usually, it does not require the problem to be differentiable as the gradient of the problem is not taken into consideration. As a result, there might be chances that PSO does not converge to optimal solution.

4.2. Ant Colony Optimization (ACO). Ant Colony Optimization (ACO) introduces an artificial algorithm motivating actual ant colonies that solve discrete optimization problem. It was first presented by Marco Dorigo in 1992 as a major aspect of his Ph.D thesis and called it the ant system [12]. While further improvements were carried out to ant colony by Gambardella Dorigo in 1997 [23]. Pseudo code for ant colony optimization is implemented with the steps as Algorithm 2.

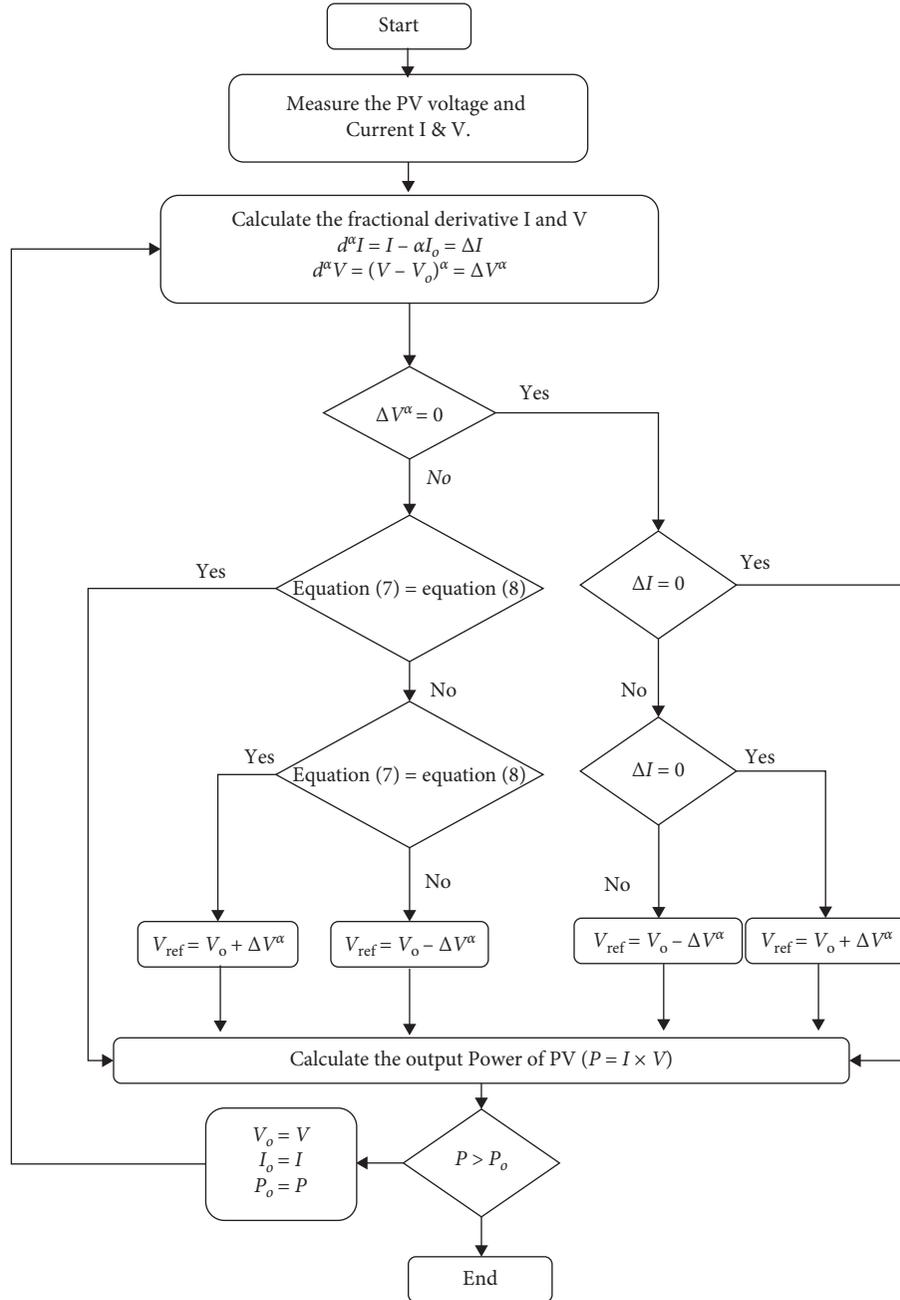


FIGURE 6: Fractional order INC MPPT flowchart.

In Algorithm 2, $\tau_{ij}(t)$ represents the intensity of trail on connection (i, j) at time t , $L(\text{ant})$ is the cost function result at each ant, and λ is pheromone decay coefficient between time $(t$ and $t + 1)$ (i.e., $0 < \lambda < 1$). Evaporation occurs in real trails, but it is too slow to play an important role. For continuous improvements it allows the search routine to forget errors and poor quality solution in favor of better ones.

4.3. AntLion Optimizer Optimization (ALO). The primary motive of ALO is the running behavior of larvae of antlions.

ALO is suggested based on the Emary and Zawbaa [24] mathematical model. The ALO algorithm simulates the interaction between the traps. The ants must move across the search area in order to model such interactions, and the antlions are permitted to chase and fit the traps. Given that ants move randomly to find food in actual life, a random walk algorithm is selected as shown in Heidari et al. [25] to model the ants' motion.

In Algorithm 3, I is a ratio, c^t is the minimum of all variables at t th iteration, and d^t indicates the vector including the maximum of all variables at t th iteration. $I = 10^w (T/t)$, where t is the current iteration, T is the

Result: MPPT parameter to achieve MPP
Initialize the PSO parameters ($N, C_1, C_2, W_{\min}, W_{\max}, V_{\max}$)
while the termination criteria not achieved (MPP) **do**
 For (each Particle i)
 Simulate and calculate the MPP and the cost function. **if** CostFunction(i) < Objective(MPP)
 then
 The Best Cost (i) = Cost Function (i)
 The Best Solution (i) = The particle (i)
 else
 The Best Cost (i) = The Best Cost ($i-1$)
 The Best Solution (i) = The Best Solution ($i-1$)
 end
 (a) Update the velocity (V): $V_i^{t+1} = V_i^t + C_1 r_1 (P_i - X_i^t) + C_2 r_2 (P_g - X_i^t)$
 where V_i^t is inertia, $C_1 r_1 (P_i - X_i^t)$ is cognitive component and $C_2 r_2 (P_g - X_i^t)$ is social component
 (b) Update the position of particles: $X_i^{t+1} = X_i^t + V_i^t$
 end

ALGORITHM 1: PSO-MPPT.

Result: MPPT parameter to achieve MPP
Initialize the ACO parameters
while the termination criteria not achieved (MPP) **do**
 For (each ant i)
 Simulate and calculate the MPP and the cost Function.
 if CostFunction(i) < Objective(MPP) **then**
 The Best Cost (i) = Cost Function (i)
 The Best Solution (i) = The particle (i)
 else
 The Best Cost (i) = The Best Cost ($i-1$)
 The Best Solution (i) = The Best Solution ($i-1$)
 end
 (a) Update pheromone for each ant: $\tau_{ij}(t+1), \Delta\tau_{ij}(t) = \sum_{\text{ant}=1}^{\text{ants}} \Delta\tau_{ij}^{\text{ant}}(t)$
 (i) Calculate the solution $\Delta\tau_{ij}^{\text{ant}}(t) = \begin{cases} (1/L_{\text{best}}) \longrightarrow & \text{if ant}(t) \text{ travels on edge}(i, j) \\ 0 \longrightarrow & \text{otherwise} \end{cases}$
 (b) Apply evaporation and globally update the ants position, according to the optimum solutions calculated earlier
end

ALGORITHM 2: ACO-MPPT.

maximum number of iterations, and w is a constant defined based on the current iteration. $X(t)$ is ant' movement, cumsum calculates the cumulative sum, n is the maximum number of iteration, t shows the step of random walk, and $r(t)$ is a stochastic function. Also, a_i is the minimum of random walk and b_i is the maximum of random walk in i th variable. R_A^t is the random walk around the antlion selected by the roulette wheel at t th iteration and R_E^t is the random walk around the elite at t th iteration. The pseudo code of ALO for MPPT developed as mentioned in Algorithm 3.

5. Modeling and Simulation Results

The proposed system has been modeled and simulated using MATLAB and Simscape software environments in order to study the system behavior and MPPT performance

with different metaheuristic optimization algorithms. The block diagram describing the total PV system with MPPT and optimizer is shown in Figure 7, where the MPPT algorithm is changed between conventional INC methods and FO-INC (fixed and variable step). The MPPT is optimized by one of the metaheuristic techniques (PSO, ACO, and ALO).

The operation sequence of PV with MPPT and optimization process is a closed loop as shown in Figure 8, and it starts with measuring the irradiance (G) and temperature (T) applied to the PV system to get the reference maximum power point from PV characteristics curves (P_{MPP}). A closed loop of PV with MPPT and Buck-Boost converter is running in Simscape environment for two seconds to measure the PV output power. The mean squared-error (MSE) between the MPP (P_{MPP}) and output power of the PV system (P_{PV}) is the cost function of the metaheuristic optimizer calculated

Result: MPPT parameter to achieve MPP

Initialize the first population of ants and antlions randomly

while the termination criteria not achieved (MPP) **do**

 For (each antlion (i))

 Select an antlion using Roulette wheel algorithm [16].

 Simulate and calculate the MPP and the cost Function. **if** CostFunction(i) < Objective(MPP)

then

 The Best Cost (i) = Cost Function (i)

 The elite (i) = The The Best Solution (i)

else

 The Best Cost (i) = The Best Cost ($i - 1$)

 The elite (i) = The Best Solution ($i - 1$)

end

 (a) Update c and d using equations: $C^t = (C^t/I)$ and $d^t = (d^t/I)$

 (b) Create a random walk and normalize it using: $X(t) = [0, \dots, \text{cumsum}(2r(t_n) - 1)]$, where $n = 1, 2, 3, \dots, n$ and $X_i^t = ((X_i^t - a_i) \times (d_i - c_i) / (d_i^t - a_i)) + c_i$

 (c) Update the position of antlions using $\text{ant}_i^t = (R_A^t + R_E^t) / 2$

 (d) Calculate the fitness of all ants according to the optimum solutions calculated earlier

end

ALGORITHM 3: ALO-MPPT.

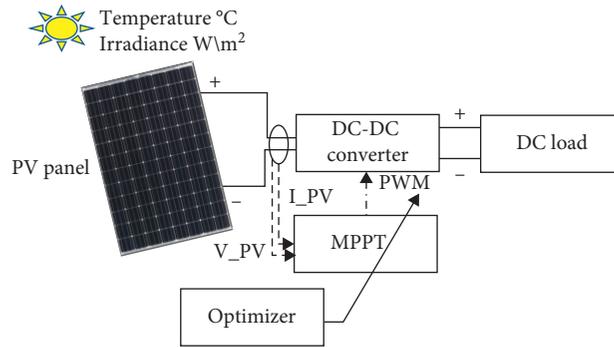


FIGURE 7: The proposed PV system with metaheuristic optimization.

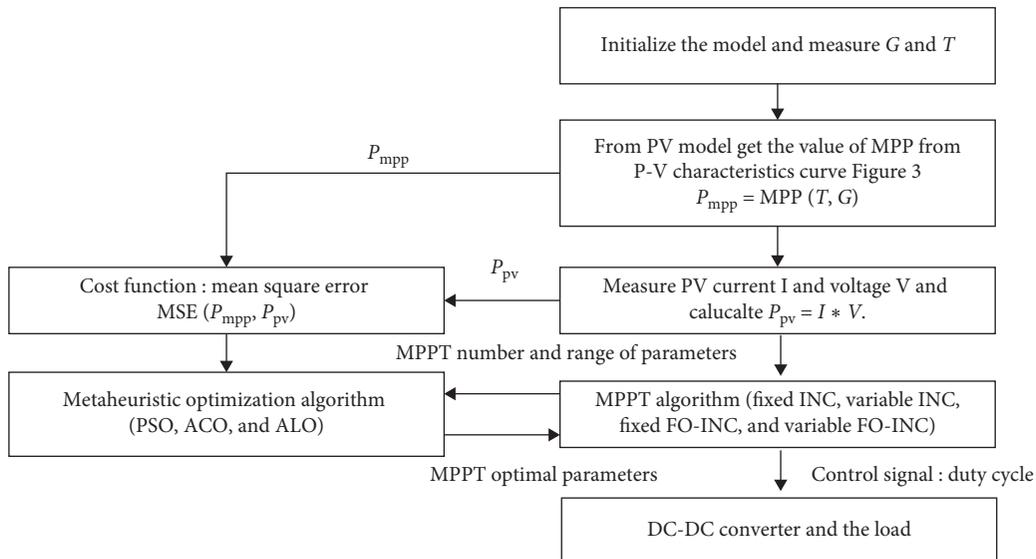


FIGURE 8: The proposed system implementation flowchart.

TABLE 3: Comparative results between MPPT algorithms at 800 W/m².

MPPT	Climatic condition							
	800 W/m ² and 25°C				800 W/m ² and 35°C			
	Max power (Watt)	MPP steps	Oscillation avg. (Watt)	No. of iterations	Max power (Watt)	MPP steps	Oscillation avg. (Watt)	No. of iterations
Fixed-step INC	321.84	137	5.87	—	319.73	131	4.92	—
Variable-step INC	324.63	125	4.89	—	319.90	127	4.17	—
FO-INC fixed step + PSO	420.28	121	4.28	100	400.01	127	4.34	100
FO-INC fixed step + ACO	470.62	115	4.067	100	462.24	121	3.089	100
FO-INC fixed step + ALO	487.22	118	3.067	100	474.24	125	3.089	100
FO-INC variable step + PSO	490.28	128	3.28	100	480.01	132	3.34	100
FO-INC variable step + ACO	510.62	115	3.067	100	490.24	121	3.089	100
FO-INC variable step + ALO	515.52	120	3.269	100	510.26	127	3.802	100

TABLE 4: Comparative results between MPPT algorithms at 1000 W/m²

MPPT	Climatic condition							
	1000 W/m ² and 25°C				1000 W/m ² and 35°C			
	Max power (Watt)	MPP steps	Oscillation avg. (Watt)	No. of iterations	Max power (Watt)	MPP steps	Oscillation avg. (Watt)	No. of iterations
Fixed-step INC	428.84	145	4.87	—	419.73	153	5.92	—
Variable-step INC	420.73	155	5.87	—	419.90	139	5.17	—
FO-INC fixed step + PSO	436.88	120	4.88	100	410.51	121	4.84	100
FO-INC fixed step + ACO	650.82	101	2.067	100	632.24	112	2.089	100
FO-INC fixed step + ALO	667.32	118	3.87	100	664.24	120	3.889	100
FO-INC variable step + PSO	590.28	86	2.28	100	580.23	92	2.34	100
FO-INC variable step + ACO	720.62	65	2.067	100	705.24	71	2.079	100
FO-INC variable step + ALO	725.32	80	2.369	100	710.63	96	2.802	100

in MATLAB environment to get the optimal MPPT parameters. The optimal parameters are applied to the chosen MPPT technique in Simscape. Performance index is calculated in MATLAB through a dynamical data exchange between MATLAB and Simscape.

The proposed MPPT contribution is generated by measuring the output energy of the PV system under different solar irradiances. Simulation was conducted when solar radiation and cell temperature change with a transient method of approximately 2 sec with 0.01 sec sampling. The characteristics of the PV array will be altered when the natural radiation and cell temperature alter, which causes the I-V curves of the PV array to change. In addition, the particular irradiance ranges from 400 to 1000 W/m² and the cell temperature ranges from 20°C to 40°C which makes it more realistic as shown in Tables 3 and 4.

Figure 9 shows the I-V and P-V curves of fixed-step INC under different temperature and radiation with small step which in return gives it better results and less oscillation; however, it takes more time to get maximum power. The variable-step INC curves, shown in Figure 10, give better results than the fixed INC. However, in variable-step INC, improper selection of the initial step size may require large number of steps to reach the MPP. Also, improper selection of the scaling factor may lead to oscillations.

The objective of PSO, ACO, and ALO is to select the best value of α for the fixed-step FO-INC and the best values of α and S for variable step to get the maximum PV power. Fixed-step FO-INC MPPT results optimized by PSO, ACO, and ALO are shown in Figure 11. Fixed-step FO-INC-PSO gives better results than conventional INC methods, less number of MPPT steps to maximum power value, and less oscillation, yet PSO optimization needs more iterations to get the

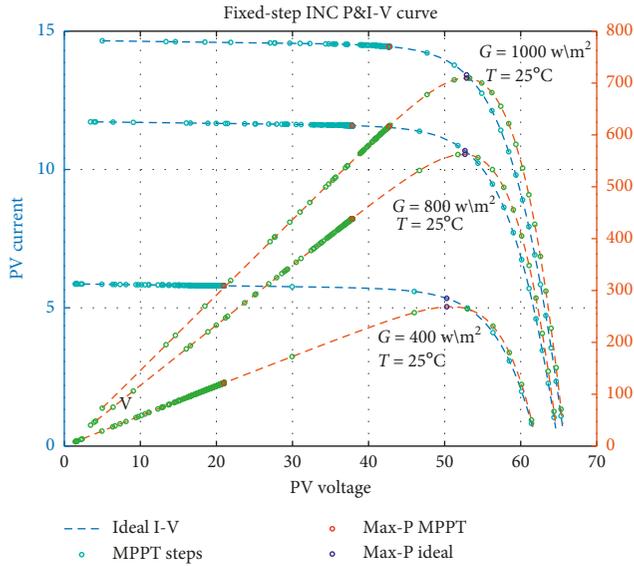


FIGURE 9: Fixed-step INC I-V and P-V curves.

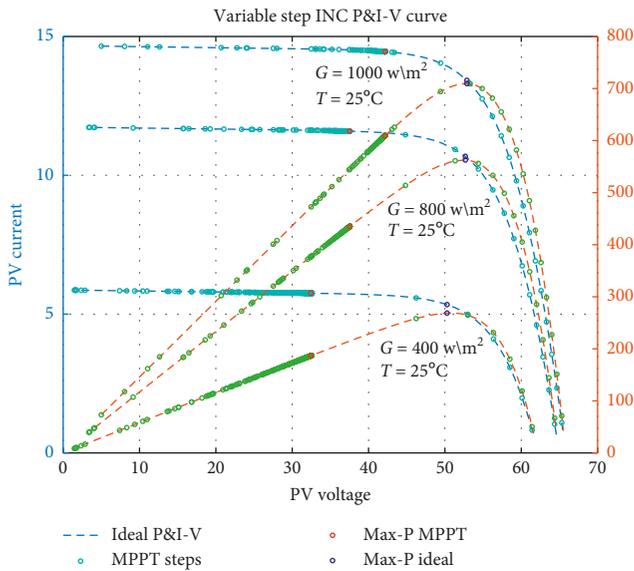


FIGURE 10: Variable-step INC I-V and P-V curves.

optimal MPPT parameter. Fixed-step FO-INC-ACO gives less number of MPPT steps than PSO and ALO, however, not the optimum parameter that can be obtained by ALO with fewer number of MPPT steps. The output power and voltage of the PV system generated using the optimization of fixed-step FO-INC-ACO gives less oscillation yet not as much maximum power as given by ALO as shown in Figure 12. Variable-step FO-INC gives better results than conventional INC and fixed-step FO-INC methods, less number of MPPT steps to maximum power value, and less oscillation. PSO needs more number of iterations than ACO and ALO to get the optimal MPPT parameters. ALO gives the optimum parameters for the maximum power with larger number of MPPT steps and vice-versa with ACO as shown in Figures 13 and 14.

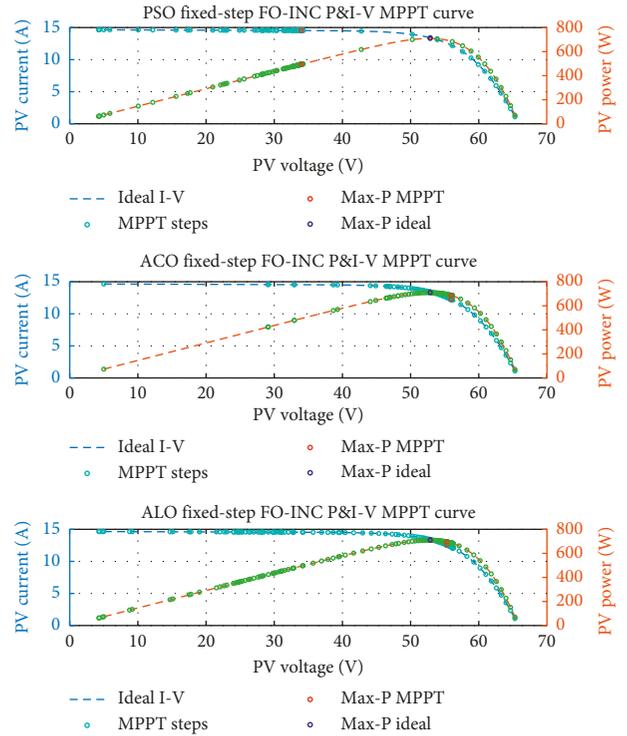


FIGURE 11: Optimization of fixed-step FO-INC I-V and P-V curves.

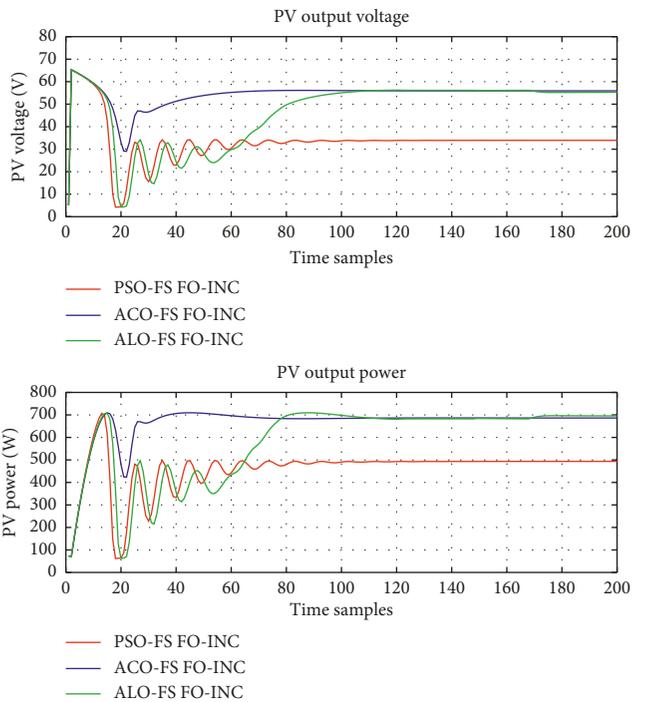


FIGURE 12: Optimization of fixed FO-INC output response.

The MPPT performance η can be monitored as in equation (10) for all the abovementioned MPPT techniques. Irradiance, temperature, power, and maximum power time waveform of the system using the proposed MPPT methods have been used

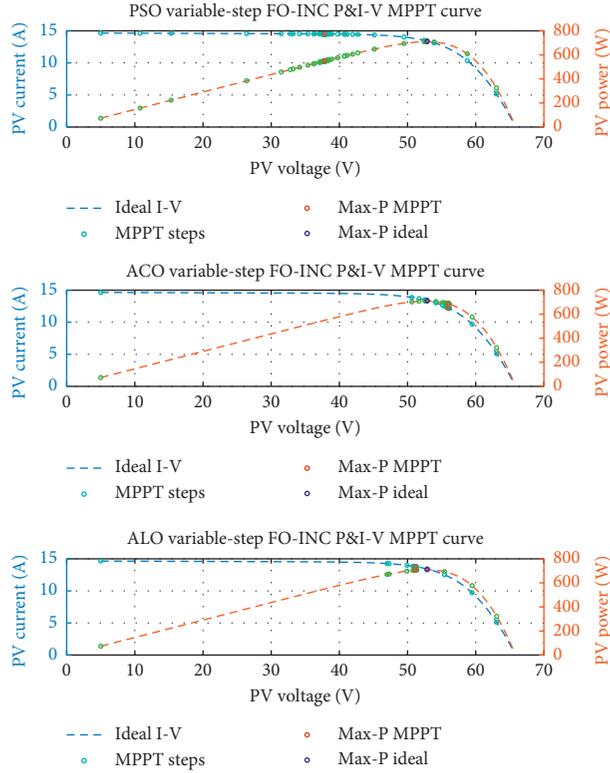


FIGURE 13: Optimization of variable-step FO-INC I-V and P-V curves.

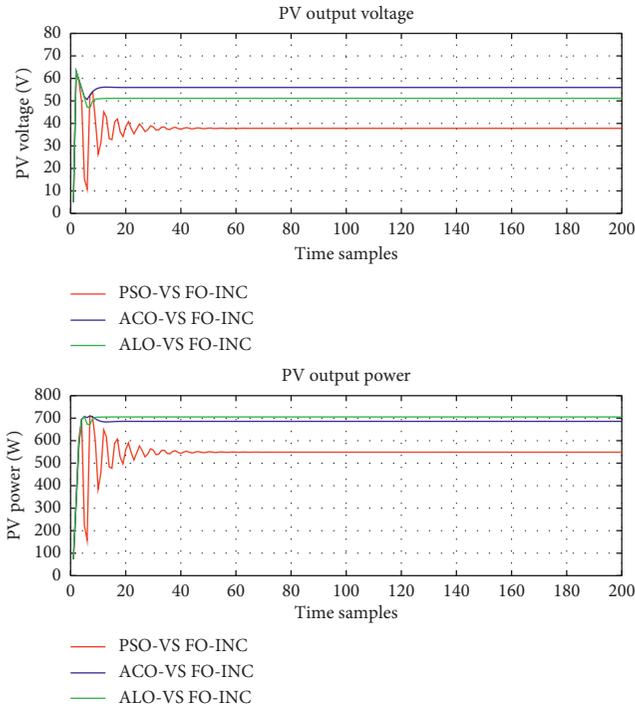


FIGURE 14: Optimization of variable FO-INC output response.

to get η . The irradiance and temperature variation mean that output power follows the highest maximum power profile very closely, and the higher performance is obtained in case of variable-step FO-INC with ALO (98.1) as noted from Table 5:

TABLE 5: MPPT algorithms efficiency.

MPPT method	Efficiency (η)
Fixed-step INC	75.9
Variable-step INC	82.1
Fixed-step FO-INC + PSO	90.2
Fixed-step FO-INC + ACO	92.3
Fixed-step FO-INC + ALO	93.2
Variable-step FO-INC + PSO	94.7
Variable-step FO-INC + ACO	97.5
Variable-step FO-INC + ALO	98.1

$$\eta = \frac{\int P_{PV}(t) dt}{P_{MPP}} \quad (10)$$

6. Conclusion and Future Work

The output power of the PV system will be changed by irradiance and temperature according to the simulation results of the system with different climatic conditions as illustrated in Tables 3 and 4. The proposed incremental fractional order FO-INC demonstrates better results than traditional INC under environmental changing processes and improves the efficiency of MPPT as FO-INC is able to provide a dynamical mathematical model for describing the nonlinear and fractional properties. The incremental change in the fractional order as a dynamic variable is used to adjust the MPPT service cycle. Using metaheuristic optimization enhances the performance of FO-INC and

provides another dynamical variable to the MPPT control. Compared to ACO and ALO, the PSO uses less number of variables and shorter calculation time for the same number of iterations. However, sometimes it cannot achieve the optimal solution. The ALO uses larger number of variables and takes the longest calculation time, yet it gives more optimal solution compared to ACO and PSO. This work could be extended by changing the resistance using another dynamical load, e.g., DC motor, or by applying different optimization techniques on the FO-INC.

Data Availability

No data were used to support this study.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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