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Research paper

An improved genetic algorithm based fractional open circuit voltage MPPT for solar PV systems

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ABSTRACT

To extract the maximum power from solar PV, maximum power point tracking (MPPT) controllers are needed to operate the PV arrays at their maximum power point under varying environmental conditions. Fractional Open Circuit Voltage (FOCV) is a simple, cost-effective, and easy to implement MPPT technique. However, it suffers from the discontinuous power supply and low tracking efficiency. To overcome these drawbacks, a new hybrid MPPT technique based on the Genetic Algorithm (GA) and FOCV is proposed. The proposed technique is based on a single decision variable, reducing the complexity and convergence time of the algorithm. MATLAB/Simulink is used to test the robustness of the proposed technique under uniform and non-uniform irradiance conditions. The performance is compared to the Perturb & Observe, Incremental Conductance, and other hybrid MPPT techniques. Furthermore, the efficacy of the proposed technique is also assessed against a commercial PV system's power output over one day. The results demonstrate that the proposed GA-FOCV technique improves the efficiency of the conventional FOCV method by almost 3%, exhibiting an average tracking efficiency of 99.96% and tracking speed of around 0.07 s with minimal steady-state oscillations. Additionally, the proposed technique can also efficiently track the global MPP under partial shading conditions and offers faster tracking speed, higher efficiency, and fewer oscillations than other hybrid MPPT techniques.

1. Introduction

Solar PV output directly depends upon the solar irradiance intensity and temperature, which are intermittent and make solar PV output highly non-linear, as illustrated in Figs. 1 and 2. Therefore, to harvest the maximum power from solar PV systems, a control unit is needed to track the maximum power point (MPP) under varying environmental conditions. Improving the maximum power point tracking (MPPT) algorithms is one of the easiest ways to improve solar PV system performance (Masoum et al., 2002).

During the previous decade, substantial efforts were made to develop new MPPT techniques (De Brito et al., 2013). A comprehensive review on the classification and performance of different MPPT techniques is presented in Karami et al. (2017), Bollipo et al. (2021). MPPT techniques can be broadly classified into three groups: offline, online, and hybrid (Reza et al., 2013). The offline methods, including constant voltage, short circuit current, and open circuit voltage track the MPP using predefined parameters calculated from PV panel characteristics and do not actually measure the PV power output during operation. Although offline methods are simple, economical, and easy to implement, they offer low tracking efficiency as they assume some parameters to be constant even under varying environmental conditions (Karami et al., 2017; Reza et al., 2013).

The lookup table technique, one of the offline MPPT methods, uses pre-saved parameters for each corresponding solar irradiance and temperature value, resulting in improved tracking speed and efficiency (Bollipo et al., 2021). In Kota and Bhukya (2016), a 2-D lookup table with maximum power point voltages for 77 combinations of irradiance and temperature levels was developed. The results demonstrated a higher tracking speed and reduced oscillations with almost the same tracking efficiency (95%) compared to the Perturb and Observe (P&O) technique. However, this technique required large memory to set up the database with 77 combinations. A comparative analysis between the lookup table and P&O was performed in Udavalakshmi and Sheik (2018). The lookup table was formed by saving the corresponding DC/DC converter's duty cycles for 70 different irradiance and temperature levels. It was found that the proposed technique exhibits a faster response than P&O with almost zero oscillations at MPP but needs large memory to save the required parameters. A hybrid variable step P&O and lookup table based MPPT technique was proposed in Sarika et al. (2020) to overcome the large

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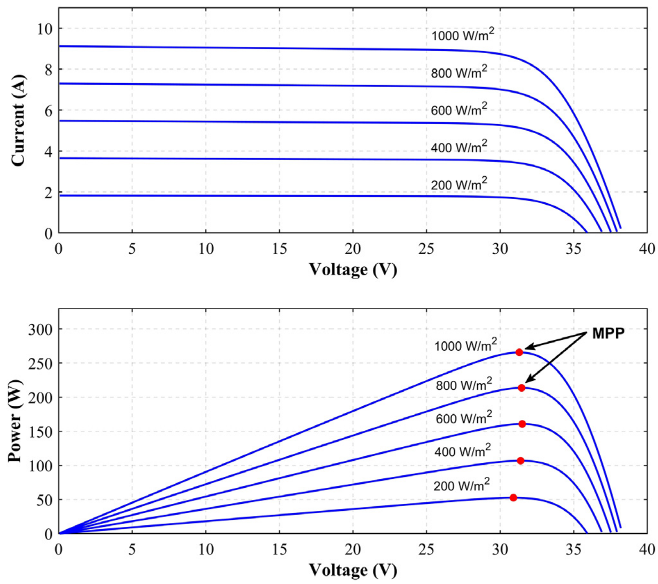

Fig. 1. I–V and P–V characteristic curves of selected PV module (MonoX LG265S1W-B3) at different irradiance levels (Electronics, 2014).

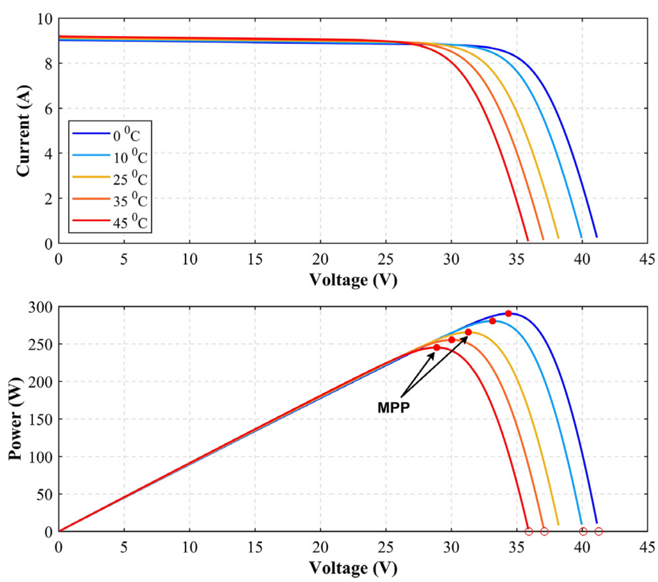

Fig. 2. I–V and P-V characteristic curves of selected PV module at different temperatures (Electronics, 2014).

memory requirement issue. Although this technique required relatively less memory, tracking speed and MPPT efficiency were also improved; the proposed algorithm depicted large oscillations, particularly at low irradiance levels. In Banakhr and Mosaad (2021), an adaptive MPPT based on a lookup table comprising PI controller parameters optimized through the Harmony Search (HS) algorithm was proposed. The results demonstrated that the proposed technique offers better performance than the conventional P&O and Incremental Conductance (IC) techniques, however, it also suffers from large memory requirement problem.

Online techniques such as P&O, Hill Climbing (HC), and IC trace the MPP by continuously adjusting the converter's duty cycle based on real-time PV power measurements (Reza et al., 2013). These techniques have been more extensively used in the literature as they provide better solution to the manufacturers. However, these techniques also suffer from some significant drawbacks. For instance, P&O leads to oscillations around MPP even after MPP has been found and results in unnecessary power loss. Additionally, it may lose its tracking direction under rapidly changing environmental conditions and is also prone to a trade-off between accuracy and speed (Desai and Patel, 2007; Jain and Agarwal, 2007). Whilst the IC technique has demonstrated better performance than P&O and exhibits very low steady-state oscillations, it requires an expensive floating-point core controller to solve the differential equations (De Brito et al., 2013). To overcome these drawbacks, some authors have reported modified P&O techniques with improved MPPT performance.

Variable perturbation steps were introduced in Wolfs and Tang (2005), Patel et al. (2009), but these techniques are not genuinely adaptive and depend on the initial user-defined step constants. In Ali et al. (2018), a modified P&O was proposed, which works by dividing the P–V curve into four regions and then adjusting the step size according to the distance from MPP. Although the tracking speed gets improved, steady-state oscillations are not fully eliminated. Additionally, tracing the operating point in one of the four sectors is challenging, especially during a rapid change in irradiance. In Ahmed and Salam (2015), an adaptive perturbation step was proposed to reduce the steady-state oscillations in the conventional P&O. At the start, an initial perturbation step size of 2% of open circuit voltage (V_{oc}) is applied, which is then gradually reduced by 0.5% during each step until 0.5% of V_{oc} is reached. Moreover, to overcome the loss of tracking direction under rapidly varying irradiance, boundary limits of $\pm$5% of V_{oc} were imposed on the operating MPP. Despite some improvements in the tracking efficiency and steady-state oscillations, this approach slows down the tracking speed due to the added complexity in the conventional algorithm. Additionally, as V_{oc} varies with varying irradiance and temperature, adjusting the perturbation step size and boundary limits on the basis of a fixed V_{oc} may lead to divergence from the true MPP. To avoid the drift problem in the conventional P&O, an extra checking condition of change in current along with the change in power was proposed in Killi and Samanta (2015). Nonetheless, this technique reduces the tracking speed due to added conditional statements and is not entirely free from steady-state oscillations.

The hybrid MPPT techniques are well-known for tracking the MPP with higher accuracy as compared to the offline or online methods. The hybrid techniques perform MPPT in two steps and employ more advanced tools such as fuzzy logic, Artificial Neural Networks, and optimization algorithms (Reza et al., 2013). During the first step, the desired parameters are first optimized using one of the previously mentioned advanced techniques. In the second step, obtained optimum parameters are used to accurately track the MPP using conventional MPPT methods. In Harrag and Messalti (2015), an improved P&O algorithm with adjustable step size was proposed, where GA was employed to tune the PID parameters such that the power output from the DC/DC converter is optimized through an adaptive duty cycle. A similar approach of optimizing PID controller parameters have also been reported in other studies (Badis et al., 2018; Lasheen et al., 2016). Although these studies reported improved performance in terms of ripple factor, response time, and overshoot, the MPPT accuracy was only marginally improved as these studies focused only on optimizing the PID controller parameters but did not consider improving the MPPT algorithm. A real-time GA based MPPT technique was developed in Hadji et al. (2018). In comparison with the conventional techniques, it was found that the proposed approach performs better in terms of accuracy, speed, and convergence. However, this technique requires the continuous measurements of both V_{oc} and short circuit current (I_{sc}) to perform the MPPT and thus needs extra sensors and pilot PV modules, incurring additional costs. In Senthilkumar et al. (2022), a comparative analysis of MPPT performance using four different optimization techniques, including Particle Swarm Optimization (PSO), GA, BAT optimization, and Grey Wolf Optimization (GWO) was performed. It was inferred that GWO offers better tracking accuracy (98%) than the other techniques. Nonetheless, the dynamic response of solar PV system under varying environmental conditions was not presented, which is critical in analysing the tracking speed, accuracy, and quality of the power produced by the developed MPPT technique. Additionally, the optimization was based on computationally exhaustive point to point scanning of the whole P–V characteristic curve. A similar approach of performing MPPT by finding the optimal duty cycle was used in Hoang (2021). The tracking efficiency of five different optimization techniques, namely PSO, GA, Differential Evolution (DE), Harmonic Search (HS), and differential PSO (DPSO) was compared. It was reported that the proposed DPSO technique outperforms the other techniques. However, testing the developed MPPT technique under different irradiance and temperature profiles was not performed. A hybrid GA-P&O based MPPT technique was proposed in Hua and Zhan (2021) to mitigate the steady-state oscillations in the conventional P&O technique. The results revealed that the proposed technique can greatly reduce the power losses occurring due to steady-state oscillations and can also track the global MPP under non-uniform irradiance conditions. However, fixed initial search points, including $0.15V_{oc}$, $0.5V_{oc}$, and $0.85V_{oc}$ were used at the beginning of optimization. Since V_{oc} also varies with irradiance and temperature, this approach raises concerns about converging to a global MPP under rapidly varying environmental conditions.

Due to their stochastic search nature, metaheuristic optimization algorithms are more dominantly being used in tracking the global maximum power point (GMPP) under partial shading (Eltamaly et al., 2018). An integrated Genetic Algorithm (GA) and P&O technique was proposed in Daraban et al. (2014) to find the global maxima for solar PV arrays under partial shading conditions. The results demonstrated that the proposed technique could efficiently locate the global MPP in the presence of local peaks. However, due to the GA search process and mutation operator, power output suffered from large oscillations at the beginning, causing significant power loss. A similar problem of large power oscillations can also be observed in the other techniques reported in Shams et al. (2020), Tey et al. (2018), Fares et al. (2021). Additionally, these techniques are not easy to implement due to the added complexity and conditional statements.

Although the previously developed modified conventional techniques and hybrid MPPT techniques offer remarkable advantages such as enhanced efficiency, better dynamic response, and improved accuracy, most are challenging to implement due to added control and complexity. Additionally, most of these methods require extra sensors and expensive controllers to implement the developed MPPT algorithms. This paper presents a simple GA based enhanced Fractional Open Circuit Voltage (GA-FOCV) method that can efficiently track the true MPP of solar PV systems under rapidly varying environmental conditions and partial shading. To overcome the unstable power output and long convergence time due to stochastic solution search in GA, a lookup table is used to save the optimal parameters and directly use them during MPPT operation. The main contributions of this work are:

(1) The proposed GA-FOCV technique is simple, cost-effective, and easy to implement. Unlike other hybrid methods, the proposed technique does not add complexity to the MPPT algorithm and is based on a single decision variable. The constrained search space introduced makes optimal solution search computationally less exhaustive and requires fewer iterations to reach the global optima.

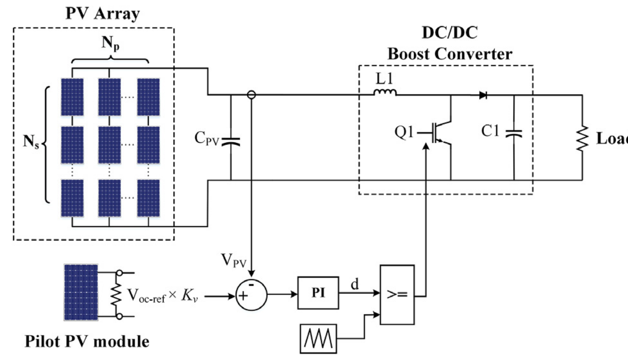

Fig. 3. Schematic of conventional FOCV MPPT technique.

(2) The proposed technique does not need any additional sensor or measurement circuitry to perform the MPPT, nor does it need any prior information about the characteristics of the installed PV modules. It works similarly to the conventional FOCV method and can be implemented using a low cost micro controller.

(3) Unlike conventional MPPT techniques, the proposed technique can accurately track the true MPP during rapidly varying environmental conditions without losing its tracking direction and is also free from steady-state oscillations. Moreover, the proposed technique can also efficiently track the global MPP in the presence of multiple power peaks during partial shading conditions.

The remainder of this paper is organized as follows. Section 2 details the methodology of the conventional FOCV and the proposed GA-FOCV technique. The simulation results and analyses are presented in Section 3, followed by conclusions in Section 4.

2. Methodology

2.1. Conventional FOCV MPPT technique

FOCV is one of the simplest and most cost-effective offline MPPT techniques, as it requires only one voltage sensor to perform MPPT (Karami et al., 2017). The conventional FOCV is based on the fact that the maximum power point voltage (V_{MPP}) is approximately a constant fraction (K_v) of V_{oc} under varying environmental conditions as presented below (Ahmad, 2010):

$$V_{MPP} = K_v.V_{oc} \tag{1}$$

If the value of K_v is known and V_{oc} of the PV array can be measured, V_{MPP} can easily be calculated from Eq. (1) and realized through the PI controller by adjusting the duty cycle of DC/DC converter as shown in Fig. 3. In Xiao et al. (2007), it was shown that K_v normally lies between 0.7–0.82. However, practically K_v mainly depends upon the PV cell characteristics and may have different values for each PV module type (Siddhant, 2014). Therefore, it is hard to choose a particular value of K_v and is usually selected by taking an average of empirical K_v measurements under varying environmental conditions. V_{oc} can be measured by periodically disconnecting a switch connected in series with the PV modules, making the output current zero and allowing measurement of V_{oc}. The PV system is then forced to work at the reference V_{MPP} calculated from Eq. (1) by using a switching converter with a feedback unit. The major disadvantage of this method is the momentary loss of power supply to the load during V_{oc} measurement. To prevent this issue, special measuring pilot PV modules having the same characteristics as other PV arrays are employed. The pilot PV module facilitates the continuous

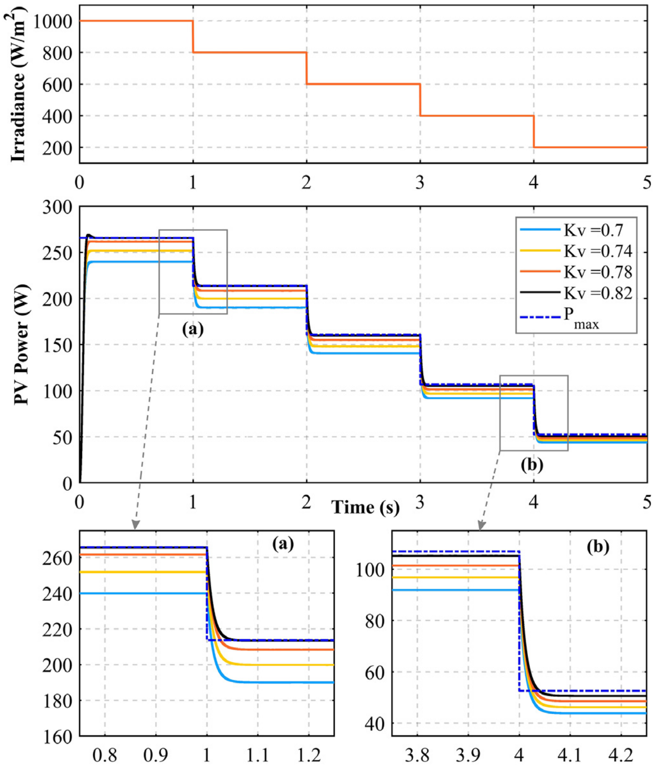

Fig. 4. PV power output from the selected PV module at different K_v under varying solar irradiance conditions.

measurement of reference open circuit voltage (V_{oc-ref}) using a separate voltage sensor as shown in Fig. 3. V_{oc} is then calculated by multiplying the measured (V_{oc-ref}) with the number of series connected solar cells for all PV modules ($N_s \times N_{array}$) and dividing the result by the number of cells connected in series in the pilot PV module.

$$V_{oc} = V_{oc-ref} \times \frac{(N_s \times N_{array})}{N_{s-pilot}} \tag{2}$$

where N_s denotes the number of cells connected in series in the PV module, N_{array} represents the total number of PV modules, and $N_{s-pilot}$ is the number of series cells in the pilot PV module.

2.2. Proposed GA based MPPT algorithm

The performance of the FOCV technique mainly depends upon the selected K_v value, which is assumed to be constant under varying environmental conditions. Fig. 4 depicts the PV power output from the selected PV module at different K_v values under varying irradiance (G) conditions. It can be witnessed that the PV power produced is greatly influenced by the selected K_v value, and the PV system may not work at its full capacity if an incorrect value of K_v is chosen. Therefore, a good approximation of K_v is crucial in extracting the maximum power from the solar PV array. This is one of the drawbacks of the conventional FOCV technique, as the selected K_v value may not be suitable for all environmental conditions and any PV module type. This can be further evidenced by Fig. 4(a) and Fig. 4(b), which show that at K_v=0.82, the PV module works very close to its theoretical maximum extractable power (P_{max}) for high irradiance levels (1000, 800 W/m^2). However, the difference between the actual PV power output (P_{PV}) and P_{max} (blue dashed line) increases at low irradiance values (1.6% at 400 W/m^2 and 3.8% at 200 W/m^2). This manifests that there may be a specific K_v value for each environmental condition which yields maximum power from the PV array. Nonetheless, the low power output using the FOCV at low irradiance levels may be insignificant for small PV systems. However, large PV systems comprising several PV arrays may incur colossal power loss. Keeping in mind the above facts, this paper presents a GA based strategy that searches for the optimal fractional constant K_v under a given environmental condition, which is then used to calculate the precise V_{MPP} from Eq. (1) and achieve MPPT with high accuracy.

GA is a type of Evolutionary Algorithm (Back, 1996) which works similarly to the process of natural evolution (Goldberg, 1989). To implement GA, the first step is to formulate the solution for the intended optimization task using numerical parameters named "chromosomes". A common approach in GA is to use a fixed length array of data types such as binary, integer, or real numbers to form the chromosome. GA then works based on an iterative set of steps, starting with a randomly generated population of solutions. The fitness score of each candidate in the population is evaluated by an objective measure called the "fitness function". A selection scheme then selects the best candidates from the current population to create a new population. The new population also referred to as a generation, is transformed by genetic operators, including crossover and mutation. Crossover exchanges genetic data between two individuals, whilst mutation offers a chance to explore previously unexplored solutions by introducing random perturbations into the values of genes. These steps of fitness evaluation, selection, and production of next generation are repeated until the specified stopping criteria, such as the desired fitness or maximum generations limit is reached.

In this work, GA is utilized to find the optimal K_v value such that the output PV power is maximized. The optimization toolbox available in MATLAB is used to solve the optimization problem formulated as follows:

$$Objective function : minimize\left\{1 / P_{PV}(X)\right\} \tag{3}$$

subject to inequality constraints:

$$0.7 \leq X \leq 0.9 \tag{4}$$

where X=K_v and P_{PV} represents the PV power output. The lower bound (0.7) and upper bound (0.9) for the decision variable (K_v) are selected such that the solution space is constrained from oversized solutions and computational time is reduced. It is worth mentioning that GA is generally programmed to minimize a function. Therefore, to achieve the maxima of a function, the original function is inverted, as shown in Eq. (3).

Setting correct GA parameters is critical in achieving the best performance in terms of computational speed and accuracy. As GA works on the basis of a randomly generated initial population, each run may converge to a different solution despite the same parameters setting. To account for this variability, a sensitivity analysis of GA parameters settings, namely, population size, maximum stall generations, and function tolerance was performed. GA was run five times with a randomly generated initial population for each selected parameter, whilst other parameters were kept at their default values. The results depicting best, worst, and mean values of computation time and optimal fitness function are displayed in Table 1.

It can be seen from Table 1 that population size=10, maximum stall generations=20, and function tolerance=1e^{-3} outputs solution with reasonable accuracy. Although a further increase in the population size and maximum stall generations may improve the accuracy (lower standard deviation), but results in considerably higher computational time. Finally, GA is computed ten times using the selected parameters (population size=10,

Table 1
Sensitivity analysis of GA parameters at G = 1000 W/m^2 (default GA settings: population size = 5, max. stall generations = 5, fitness function tolerance = 1e^{-1}).

GA parameters	Simulation time (s)			Optimal fitness function (max. P_{PV} (W)			
	Best	Worst	Mean	Best	Worst	Mean	Standard deviation
Population size							
5	140	158	145	265.64	261.95	263.63	1.7794
10	307	332	325	265.63	265.39	265.34	0.4551
15	482	504	494	265.62	265.35	265.53	0.1079
20	658	680	668	265.63	264.81	265.4	0.3388
Maximum stall generations							
10	246	250	248	265.55	264.88	265.32	0.2815
15	348	354	352	265.64	265.3	265.52	0.1416
20	448	459	451	265.62	265.55	265.59	0.0313
25	547	571	555	265.63	265.57	265.59	0.0313
Function tolerance							
1e^{-2}	147	148	147	265.59	263.49	264.88	0.8488
1e^{-3}	146	152	148	265.57	263	264.81	0.7321
1e^{-4}	147	151	149	265.6	264.11	265.14	0.6511
1e^{-5}	147	149	148	265.62	262.33	264.47	1.5401
Selected parameters-10 runs (Population size = 10, max. stall generations = 20, function tolerance = 1e^{-3})							
	1006	1047	1025	265.64	265.62	265.62	0.0119

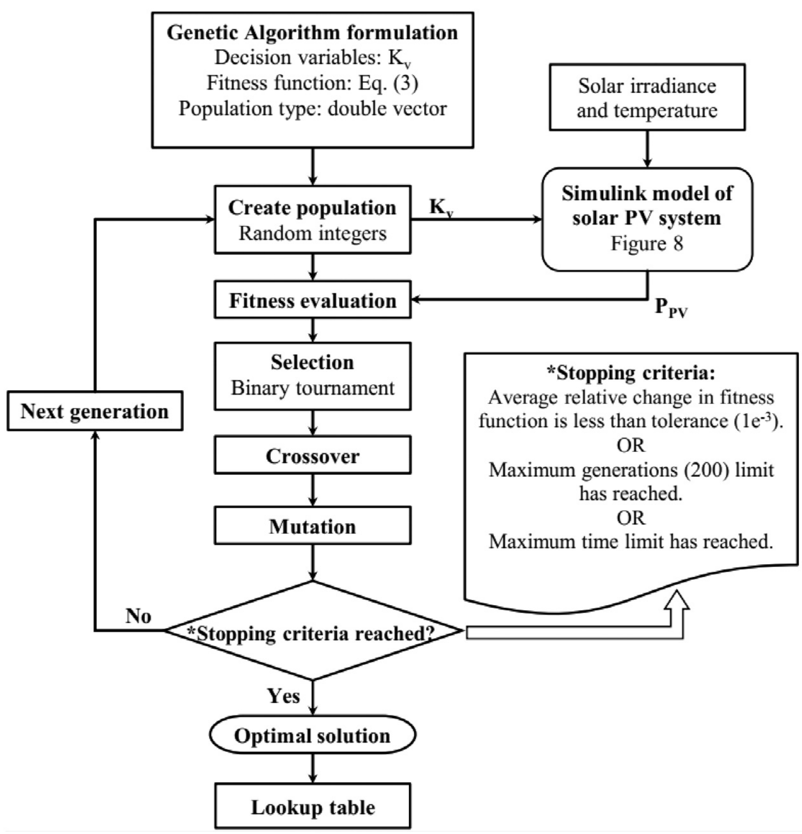

Fig. 5. Optimization workflow representing GA setup, data inputs, and outputs.

maximum stall generations=20, and function tolerance=1e^{-3}), reporting around 1% standard deviation in the final optimum fitness function values, which depicts appropriate GA parameters selection.

The workflow of the whole methodology depicting different steps involved in the optimization process is illustrated in Fig. 5. At first, a randomly generated population of potential candidate solutions is created, and each candidate's fitness (P_{PV}) is evaluated by simulating the solar PV system model built in Simulink. The first generation then goes through selection, crossover, and mutation operators to create the next generation. This process is repeated until the stopping criteria for optimal solution are met. The overall optimization process showing the convergence of GA to an global optimal solution for one of the test cases (G=1000 W/m^2) is illustrated in Fig. 6. It can be seen that at the start, the initial population shown in black filled circles is dispersed across the specified solution space, which evolves with time over the successive generations and eventually converges to an optimal solution of K_v=0.82 at which theoretical maximum P_{PV}= 265.6 W is produced. Since GA is a stochastic search process and evolves over successive generations, it may slow down the MPP tracking speed and even cause significant oscillations in

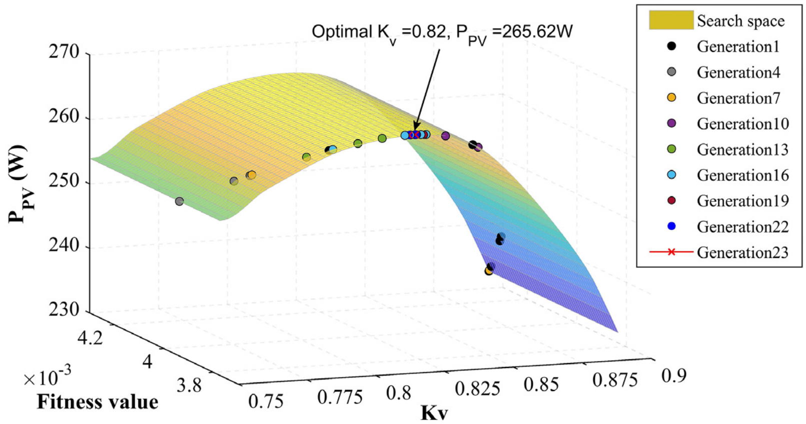

Fig. 6. GA optimal solution search at G=1000 W/m^2.

the power output at the start of the solution search. This is further illustrated in Fig. 7, which depicts that the GA search process starts with a highly diverse population which eventually converges to the optimal value over successive generations and outputs a distinct optimal K_v for each irradiance condition. Therefore, to avoid the above mentioned issues, a lookup table is used to save the required optimal K_v values and directly output them during MPPT. Optimizations are performed for irradiance varying from G=1000 W/m^2 to G=200 W/m^2 with a step difference of 200 W/m^2, and the optimal K_v values obtained are saved in a 1-D lookup table with V_{oc} as inputs so that no extra irradiance or temperature measuring equipment is required.

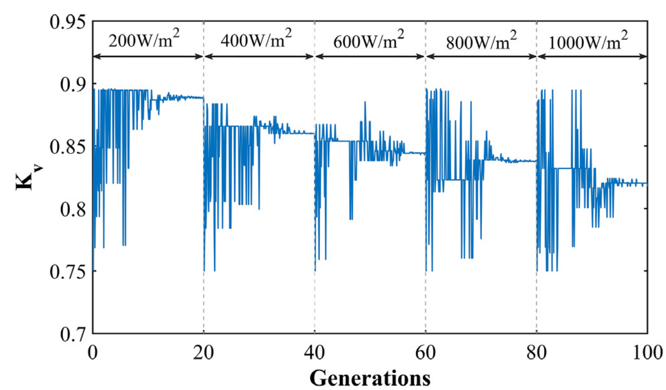

Fig. 7. Evolution of K_v values over generations for step changes in irradiance.

2.3. PV system modelling

To model the solar PV, the PV array block available in the Simulink/Simscape Electrical is utilized. Through this block, the user can set the number of PV modules in series or parallel and select a preset PV module type from a range of PV modules available in the National Renewable Energy Laboratory (NREL) System Advisory Model (Blair et al., 2018). For this study, a commercial PV module (Manufacturer: LG Electronics, Model Name: MonoX, LG265S1W-B3) with nominal power of 195 W and area of 1.64m^2 was selected (Electronics, 2014). The current output for a single module is calculated as (Gow and Manning, 1999):

$$I(t) = I_L(t) - I_d(t) - \frac{V(t) + I(t)R_s}{R_{sh}} \tag{5}$$

where I_d represents diode saturation current, R_s denotes series resistance, and R_{sh} is the shunt resistance. The photocurrent $I_L(t)$ depends directly upon the solar irradiance (G) and cell temperature (T_{cell}).

$$I_L(t) = \frac{G(t)}{G_{STC}}\left[I_{L,STC} + K_i\left(T_{cell}(t) - T_{STC}\right)\right] \tag{6}$$

In Eq. (6), K_i denotes the temperature coefficient (A/^{0}C), G_{STC} is the solar irradiance at standard test conditions (1000 W/m^2), and T_{STC} represents reference cell temperature at standard test conditions (25 °C). The diode current $I_d(t)$ is calculated as:

$$I_d(t) = I_o\left[exp(\frac{V_d}{V_T}) - 1\right] \tag{7}$$

I_o represents diode reverse saturation current and V_d is the diode voltage. The thermal voltage V_T can be found as:

$$V_T = \frac{kT}{q} \times nI \times N_{cell} \tag{8}$$

In Eq. (8), k is the Boltzmann constant (1.308×10^{-23}J/K), q represents the charge of an electron (1.6022×10^{-19}C), nI is the diode ideality factor (around 1.0), and N_{cell} stands for the number of series connected solar cells. To adjust the PV output terminal voltage (V_{PV}) in accordance with the V_{MPP} found from Eq. (1), a DC/DC boost converter is employed that acts as a decoupling unit between the PV array and the load (R). The duty cycle (d) of the boost converter is regulated by a PI controller such that the V_{PV} is maintained close to V_{MPP}. The relationship between the voltage output (V_{out}) from the boost converter and the duty cycle can be expressed as:

$$V_{out} = \frac{V_{in}}{1-d} \tag{9}$$

The power output (P_{out}) from the PV system can be calculated as (Perelmuter, 2017):

$$P_{out} = \frac{V_{out}^2}{R} = \frac{V_{in}^2}{R(1-d)^2} = P_{in} \tag{10}$$

So, if V_{out} is aligned with V_{MPP} and converter losses are neglected, maximum $P_{PV}(t)$ is delivered. The system architecture described above is modelled using MATLAB/Simulink and is shown in Fig. 8. The parameters of the PV system components used in this study are provided in Table 2. The instantaneous tracking efficiency of the proposed MPPT technique is calculated as follows:

$$\eta_{MPPT} = \frac{P_{PV}(t)}{P_{max}(t)} \times 100 \tag{11}$$

In Eq. (11), $P_{PV}(t)$ is the actual PV power produced at time t and $P_{max}(t)$ is the maximum theoretical power that can be achieved from the PV array at time t.

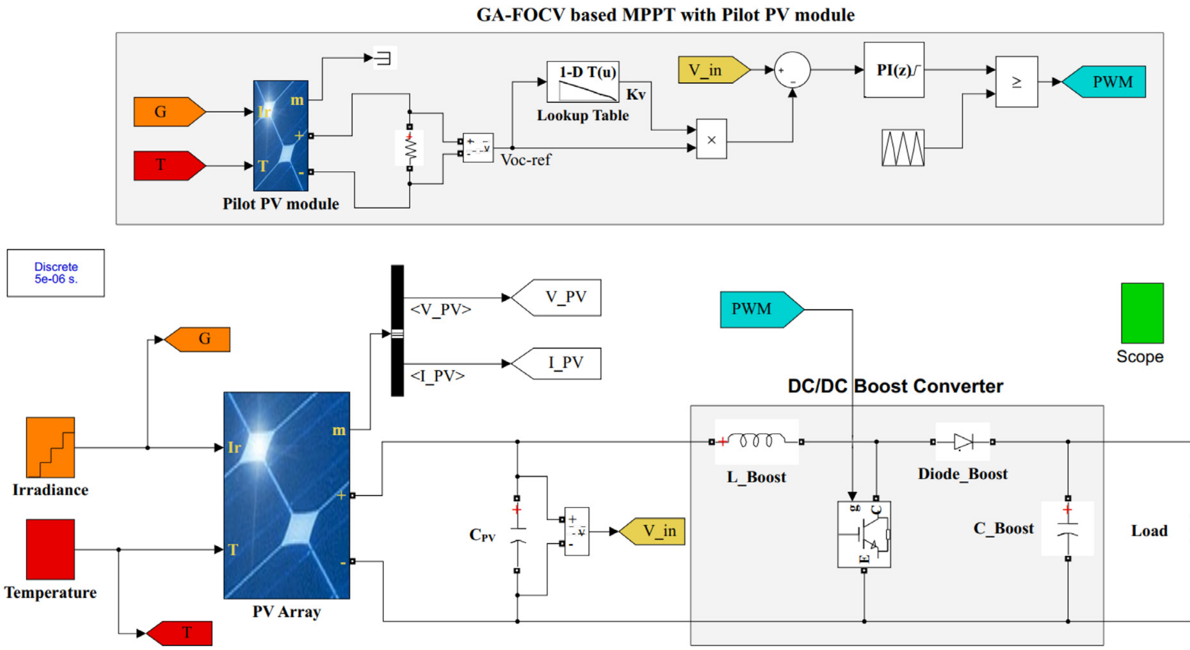

Fig. 8. Simulink diagram of PV system with proposed MPPT schematic.

Table 2
Specifications of PV system components.

Parameter	Value
PV module type	LG265S1W-B3 (Electronics, 2014)
Cell type	Monocrystalline
Number of cells	60
Switching frequency	10 kHz
Number of parallel strings	1
Series modules per string	1
PV output capacitor (C_{PV})	10 mF
Boost inductor (L_{boost})	1 mH
Boost capacitor (C_{boost})	1 mF
Controller proportional constant	2
Controller integral constant	0.001
Load	25 Ω

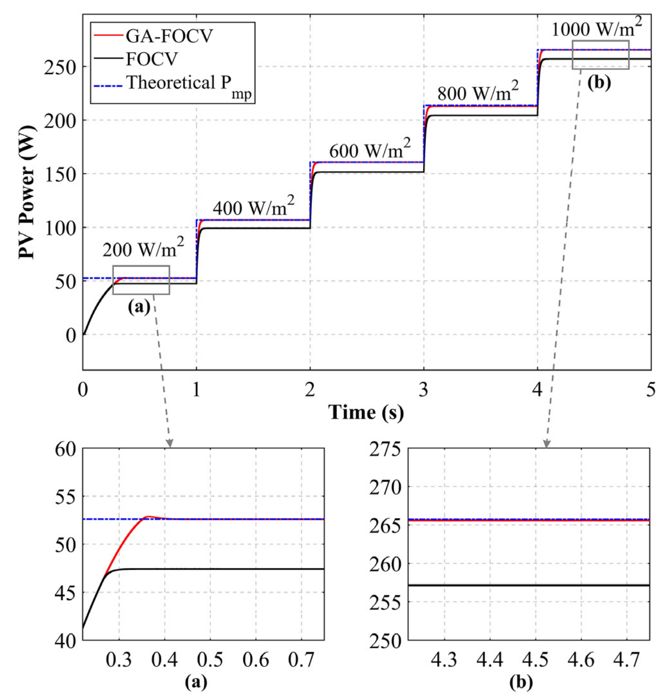

Fig. 9. Comparison between conventional FOCV and proposed GA-FOCV under step changes in irradiance.

3. Results and discussion

A GA based strategy is proposed to find the optimal fractional constant (K_v) in the FOCV MPPT technique to maximize PV power for the given input conditions. The PV system model comprising solar PV arrays, DC/DC boost converter, an MPPT controller, and a resistive load is developed in MATLAB/Simulink. The performance of the proposed MPPT approach is evaluated by performing the simulations using different solar irradiance profiles and comparing the outcomes with the conventional FOCV, P&O, and IC MPPT techniques.

3.1. Performance under step changes in irradiance

Fig. 9 depicts the performance of the conventional FOCV MPPT technique with fixed average K_v=0.76 compared with the GA based FOCV (GA-FOCV) which uses optimal K_v from lookup table. The MPPT performance of both techniques is tested under sudden step changes in the irradiance levels every second, starting from 200 W/m^2, while the temperature is assumed to be constant (25 °C). The results shown in Fig. 9 reveal that the GA-FOCV outperforms the conventional FOCV under all input conditions. At G=200 W/m^2 (0-1s), the maximum extractable power P_{max} (blue dashed line) is 52.6 W. During this interval, the maximum power output from the conventional FOCV (black line) is 47.4 W, whilst the power produced by GA-FOCV (red line) is around 52.59 W as shown in Fig. 9(a). Similarly, at 1000 W/m^2 (4-5s), shown in the zoomed portion Fig. 9(b), the P_{max} is 265.7 W, and the power output from GA-FOCV is around 265.6 W. However, the conventional FOCV falls behind and produces only 257.3 W during this time interval. Likewise, for all other irradiance conditions, it can be witnessed that the GA-FOCV produces power in very close proximity to the P_{max}, while the conventional FOCV fails to track the true MPP. Fig. 10 depicts the instantaneous MPPT efficiency

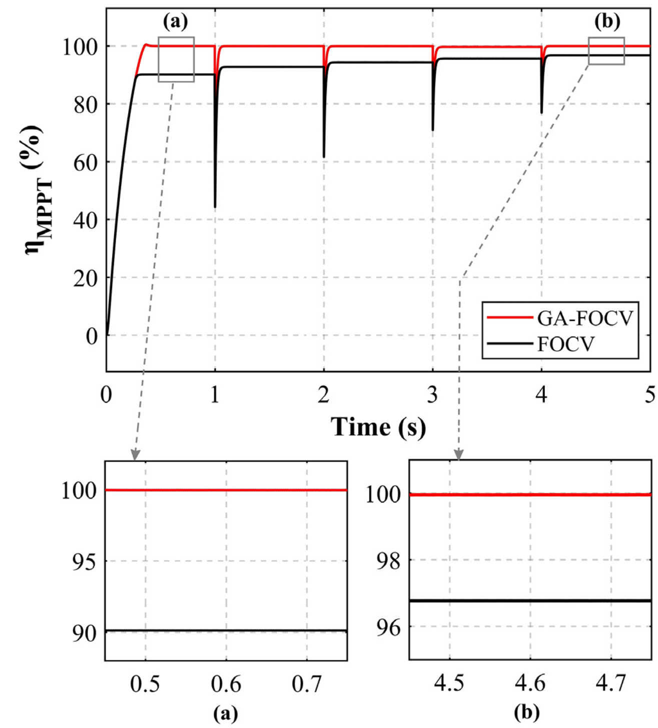

Fig. 10. Comparison between MPPT efficiency of conventional FOCV and proposed GA-FOCV.

(η_{MPPT}) of FOCV and GA-FOCV techniques, calculated by using Eq. (11). The η_{MPPT} for GA-FOCV is found to be almost 100% (minimum: 99.65% at 800 W/m^2, maximum: 99.96% at 200 W/m^2), whereas for the conventional FOCV, maximum η_{MPPT} achieved is 96.7% at 1000 W/m^2 as displayed in Fig. 10(b). A sudden drop in the efficiency for a few microseconds after every 1s interval (step change in irradiance) is due to the PI controller. Moreover, as discussed previously in Fig. 4 and from Fig. 9, it can be noticed that the η_{MPPT} for conventional FOCV is worst at low irradiance levels and improves with the rise in irradiance. In comparison, the proposed GA-FOCV successfully tracks the true MPP with almost 100% accuracy, even under low irradiance conditions. It can be inferred from the above results that assuming a constant K_v under varying environmental conditions is a simple approach but inefficient. On the other hand, the proposed approach maximizes the PV power output by using the global optimum K_v for each given input condition, thus significantly enhancing the η_{MPPT}.

3.2. Comparison with conventional techniques

For comparison, the performance of the developed GA-FOCV technique is evaluated against the most commonly used MPPT techniques, including P&O and IC. For P&O, the perturbation step size of 1e^{-4} was selected for simulations. From Figs. 11 and 12, it can be witnessed that the proposed GA-FOCV is superior in performance compared to both P&O and IC methods. As displayed in Fig. 12, the tracking efficiency of P&O at low irradiance levels is very poor and can be as low as 30% at 200 W/m^2. Although the performance of P&O improves at high solar irradiance levels as shown in Fig. 11, it suffers from significant steady-state oscillations due to the fixed perturbation step size as shown in the zoomed portion Fig. 11(d). Conversely, the IC technique exhibits very low steady-state oscillations and has better tracking efficiency than P&O, even at low irradiance conditions. Nonetheless, its tracking performance is still no match to the GA-FOCV and

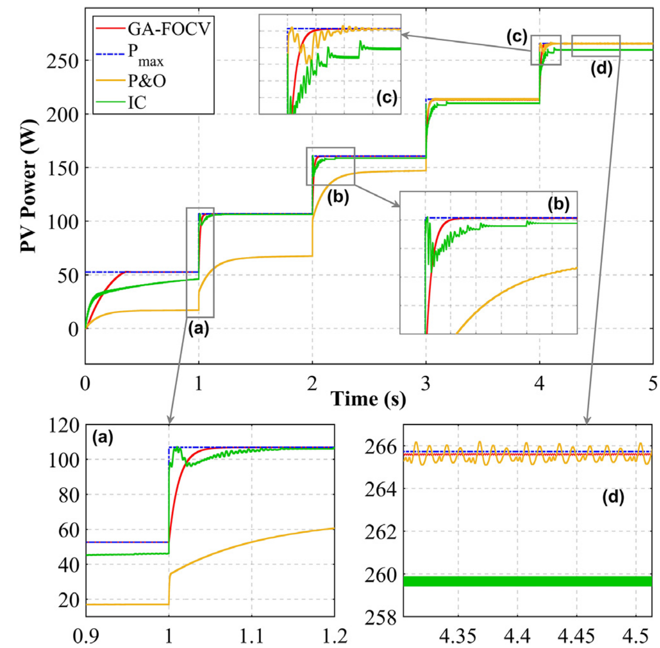

Fig. 11. Comparison of GA-FOCV with P&O and IC techniques.

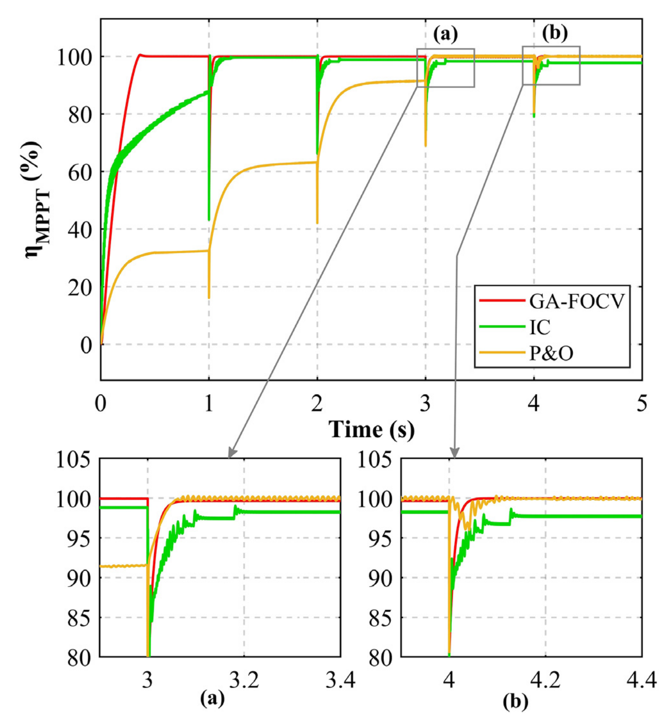

Fig. 12. MPPT efficiency comparison between GA-FOCV, P&O, and IC techniques.

varies with environmental conditions. Additionally, IC also suffers from a slow tracking speed of around 0.2s as depicted in Fig. 12(a) and Fig. 12(b), whilst the proposed GA-FOCV demonstrates faster tracking speed=0.07s under step change in irradiance and almost perfectly tracks the true MPP under all conditions.

3.3. ROPP test

In the previous results, an irradiance profile with a sudden step change was applied, which may not reflect the actual environmental conditions as solar irradiance is highly intermittent.

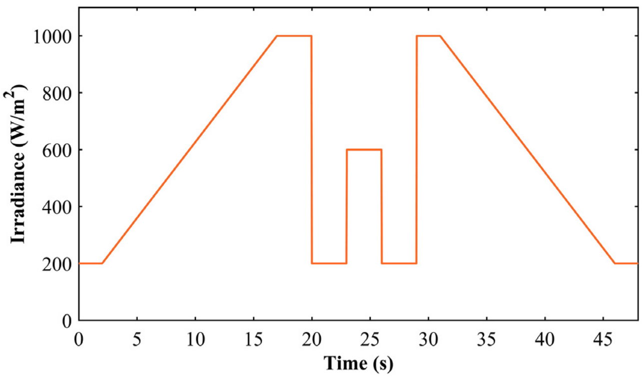

Fig. 13. Irradiance profile for ROPP test.

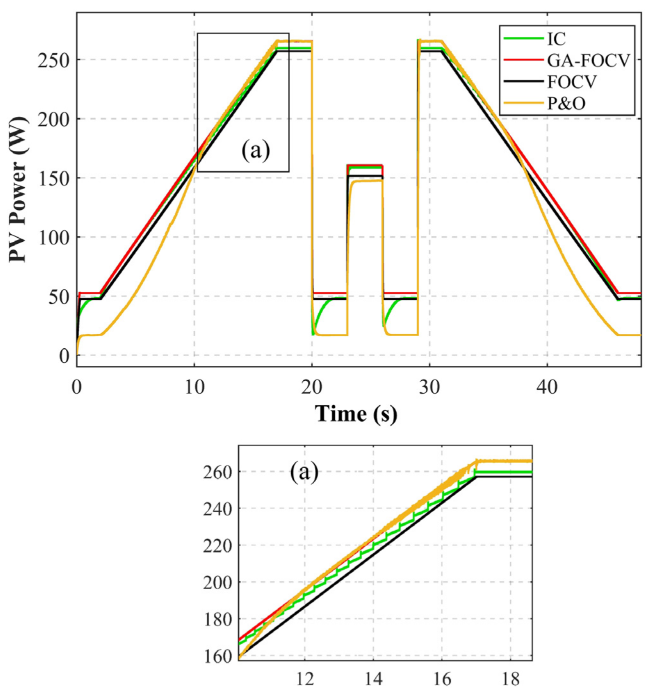

Fig. 14. Comparison of GA-FOCV with conventional MPPT techniques under ROPP test.

Therefore, the performance of MPPT algorithms is often tested against different irradiance profiles. The Ropp test was proposed by Ropp et al. (2011) and is based on the irregular irradiance profile shown in Fig. 13. This test was developed to check whether the MPPT control can handle sudden step changes and a gradual change in irradiance. The profile starts at G=200 W/m^2 and gradually rises to 1000 W/m^2 during 2-17s. Afterwards, four step changes are introduced: 1000–200 W/m^2, 200–600 W/m^2, 600–200 W/m^2, and 200–1000 W/m^2. Finally, the irradiance gradually decreases from 1000 W/m^2 to 200 W/m^2 during 31-46s. A comparison of tracking performance for the proposed GA-FOCV method and other conventional techniques under the Ropp test is presented in Fig. 14.

It can be witnessed that the proposed GA-FOCV technique shows the best performance compared to other conventional techniques. During the slow ramp up (2-17s) and slow ramp down period (31-46s), P_{PV} from GA-FOCV also increases or decreases linearly with the irradiance. In contrast, the P&O fails to track the true MPP during gradually varying irradiance conditions and perturbs in the wrong direction resulting in considerable power loss. However, IC demonstrates better performance than P&O and does not lose its tracking direction during irradiance ramp up and ramp down period. However, it experiences large oscillations as shown in Fig. 14(a). Although the conventional FOCV (black line) exhibits better dynamic response and produces more stable power output than P&O and IC techniques, it suffers from the drawback of comparatively lower MPPT efficiency. In contrast, the proposed GA-FOCV exhibits excellent performance under Ropp test, efficiently tracks the true MPP with minimal oscillations and never loses its MPP locus.

Table 3
Specifications of experimental setup.

Component	Description
PV array	
Type	LG265S1W-B3 (Electronics, 2014)
Modules in series per string	12 (12 × 265 W = 3.1 kW)
Parallel strings	1
Inverter	
Type	Sunny Boy3000HF (SMA, 2021)
Max. DC power	3.15 kW
MPP voltage range	210–560 V
Max. input current	15 A
Rated power output	3 kW
Rated frequency/voltage	50 Hz/230 V

3.4. Performance using one day irradiance and temperature profile

To test the robustness, PV power output from the proposed MPPT technique is compared with the power produced by a real PV system over one day (12 h). The PV system used for the test case is installed at Edith Cowan University, Joondalup, Western Australia and comprises solar PV arrays, inverters, charge controllers, and a data acquisition system as shown in Fig. 15 and specifications given in Table 3. The solar irradiance and temperature data required for simulations is acquired from the weather station facility and is recorded with a temporal resolution of 15-minutes, including intermittency due to the passing clouds as shown in Fig. 16. It can be seen that the solar irradiance and temperature increase almost linearly from 6:00 am until midday (1:00 pm) and then gradually decrease during the rest of the day. To compare the performance of the proposed GA-FOCV with the actual PV system (Fig. 15), the same size for the PV array (series modules=12) in the Simulink model (Fig. 8) was selected and simulations were performed by using the irradiance and temperature profile (Fig. 16) with a step change of 1s. The results shown in Fig. 17 depict that the performance of the proposed GA-FOCV is comparable to the power output from the actual PV system. However, it outmatches conventional techniques and outputs considerably higher power, especially during low and medium irradiance conditions. For instance, around 7:50 am, when the irradiance is about 200 W/m^2, the power output by P&O and IC is only around 220 W, while the power harvested by GA-FOCV is approximately 730 W. Similarly, around 10:00 am (irradiance =550 W/m^2), the power produced by GA-FOCV is around 2100 W, whilst the power output from P&O and IC is about 1700 W. Considering that solar PV systems have a lifetime of approximately 25 years, this improvement in extracting the maximum power output is significant and can lead to enhanced economic benefits.

Additionally, the conventional P&O and IC techniques are also prone to loss of tracking direction and oscillations, whilst the GA-FOCV almost perfectly tracks the maximum power locus. Unlike the conventional FOCV technique, the developed GA-FOCV technique does not need any specific information about the PV module type for MPPT. These advantages provide a significant impetus for considering the application of the proposed GA-FOCV MPPT technique over conventional techniques.

Fig. 15. PV system facility installed at Edith Cowan University.

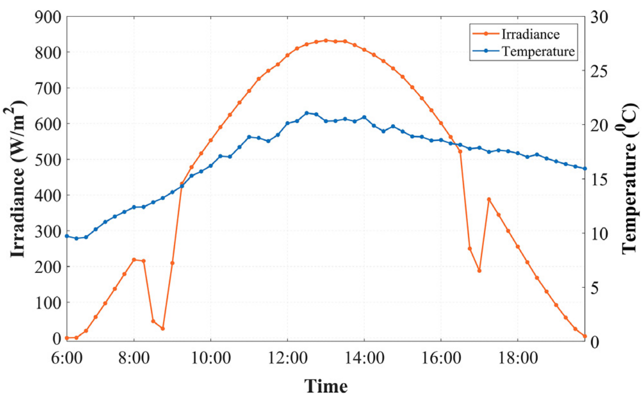

Fig. 16. Irradiance and temperature profile for a typical day during summer.

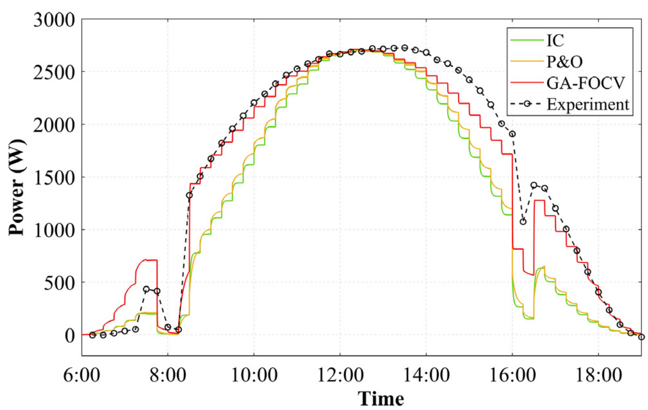

Fig. 17. Performance of GA-FOCV in comparison with real PV system and conventional MPPT techniques during a typical day.

3.5. Performance under partial shading conditions

In large solar PV systems, PV modules are connected in series and parallel to increase the output voltage and current, respectively. Due to the large surface area covered in such systems, some PV modules may get exposed to non-uniform irradiance due to passing clouds, nearby buildings, or trees. Under such conditions, partially shaded PV modules output lower current than the rest of the PV modules and begin to absorb power, which is dissipated as heat resulting in a hot spot. If the junction temperature is not controlled, this may lead to a permanent damage to the PV modules. To protect the solar panels from partial shading effects, bypass diodes are usually employed such that the solar panels producing lesser current in the string are shunted. Due to the bypass diodes, overall PV power output decreases and multiple local maximum power points (LMPP) along with a global maximum power point (GMPP) appear on the P–V characteristic curve, posing serious challenges to the MPPT controllers for tracking GMPP (Silvestre et al., 2009).

The viability of the proposed GA-FOCV technique is tested under partial shading conditions by using a PV array comprising eight modules in series and two in parallel. Since bypass diodes become active only when any PV module is producing less current compared to other modules in the array, this approach is used to detect the partial shading condition such that if the bypass diode starts conducting, the corresponding K_v value for partial shading conditions is used rather than the K_v during normal irradiance conditions.

The P–V characteristic curves and the system's dynamic response during partial shading are displayed in Fig. 18(a) and Fig. 18(b), respectively. A uniform irradiance of 1000 W/m^2 is applied to all PV modules at the beginning of the simulation. At t = 0.5s, one module is partially shaded by G = 200 W/m^2 (case-a), and at t = 1s, another module is also shaded by G = 200 W/m^2 (case-b). It can be observed that the proposed GA-FOCV can also successfully track the GMPP during partial shading and produces around 3,697 W for case-a, which is very close to the theoretical maximum power depicted in Fig. 18(a). Similarly, the PV power produced in case-b equals the maximum achievable power of 3,155 W. On the other hand, the MPPT controller fails to track the GMPP and gets stuck at LMPP if partial shading goes undetected and optimal K_v values are not used. An interesting fact found in this analysis is that during partial shading, the known range of K_v (0.7–0.82) mentioned by Xiao et al. (2007) no longer holds; instead, the optimal K_v is found at 0.71 for case-a and 0.6 for case-b.

To further validate the performance of the proposed approach, three different partial shading patterns are simulated. Fig. 19 shows the P–V curves and the performance of the proposed technique for each shading pattern. In the first partial shading pattern, referred to as case-1, four modules are illuminated with G = 1000 W/m^2, and four are at G = 150 W/m^2. As shown in Fig. 19(a), there are two peaks in this shading pattern, and GMPP lies at 2,071 W, which is successfully tracked by the proposed technique in less than 0.1s. In case-2, three modules are exposed to G = 1000 W/m^2, three modules are at G=500 W/m^2, and two modules are illuminated with G = 150 W/m^2, resulting in GMPP = 1,721 W located in between the other two peaks. As shown in Fig. 19(b), the proposed technique tracks the GMPP (1,721 W) within 0.6s. In the third partially shading condition (case-3), two modules are at G = 1000 W/m^2, two modules at G = 600 W/m^2, two modules at G = 300 W/m^2, and the remaining two at G = 150 W/m^2. For this condition, there are four power peaks and GMPP is located at 1,346 W as shown in Fig. 19(a). Fig. 19(b) depicts that the proposed technique can accurately track this GMPP (1,346 W) within 0.1s. Thus, it can be inferred from these results that the proposed GA-FOCV technique has the capability to accurately and speedily track the GMPP under partial shading conditions.

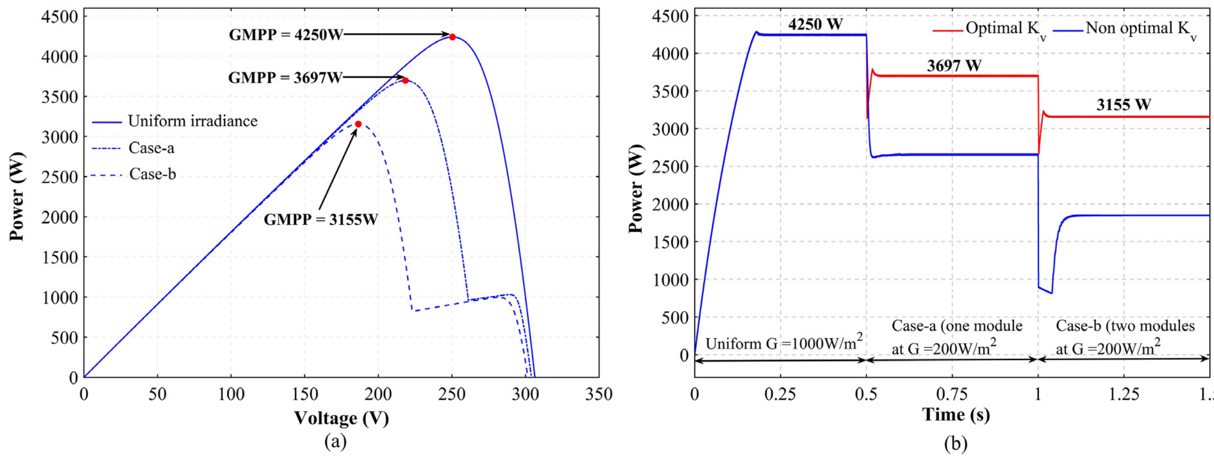

Fig. 18. (a) P–V characteristic curves under partial shading, (b) power output from the PV array.

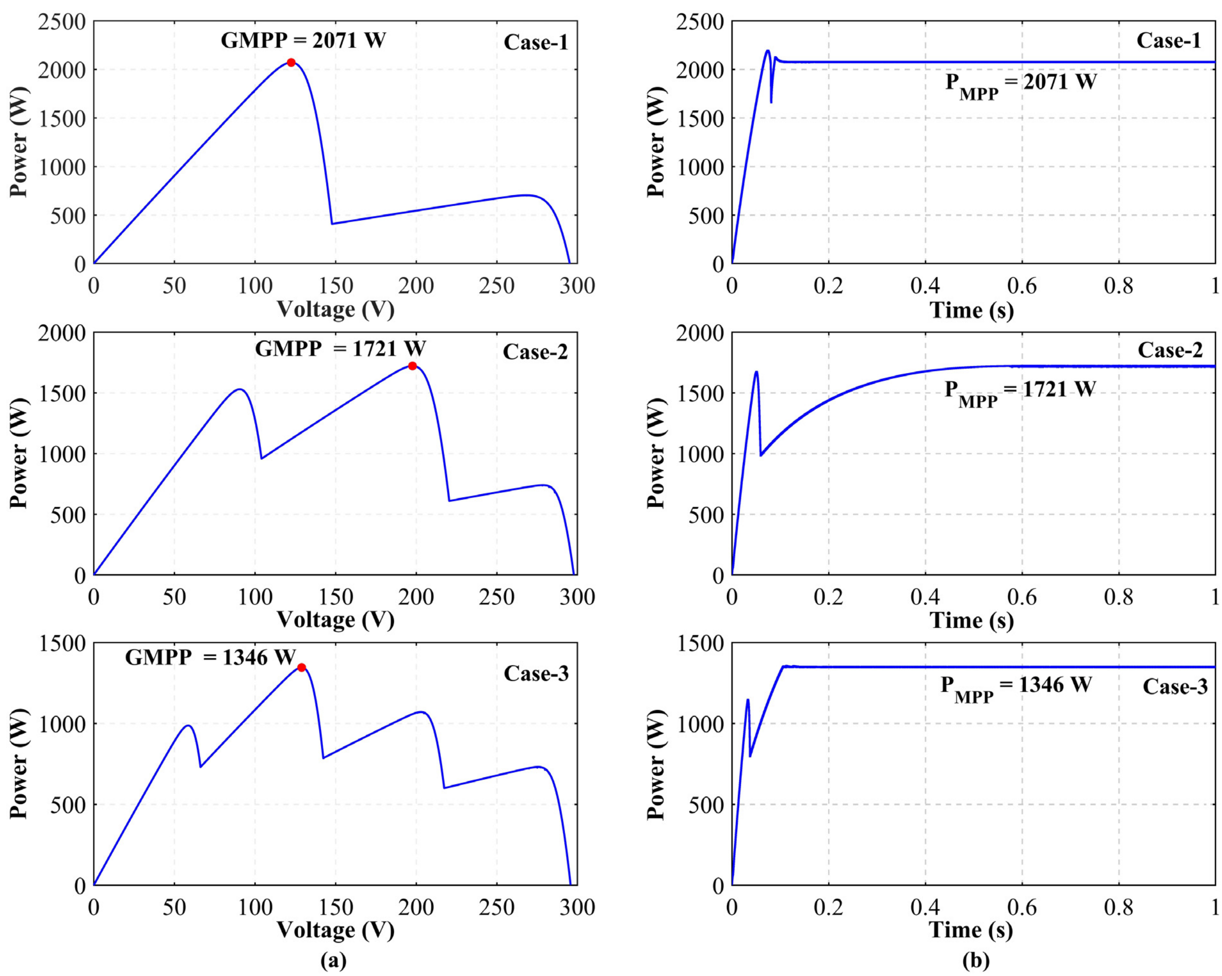

Fig. 19. (a) P–V characteristic curves for different partial shading patterns (b) Power output from GA-FOCV at different partial shading conditions.

3.6. Comparison with previous studies

A comparison between the performance of the proposed technique and some recently published similar techniques is presented in Table 4. Although lookup tables based approaches reported in Malathy and Ramaprabha (2013), Kota and Bhukya (2016), Udavalakshmi and Sheik (2018), Sarika et al. (2020), Banakhr and Mosaad (2021) offer improved tracking speed and steady-state oscillations, they suffer from low tracking efficiency of around 95%. Additionally, the lookup tables built in these studies require solar irradiance and temperature as inputs, necessitating large memory to save the required parameters. Moreover, extra arrangements are also needed for measuring the irradiance and temperature. On the other hand, the proposed GA-FOCV does not need extra irradiance or temperature measuring equipment for the lookup table and performs MPPT using V_{oc} measured from an already installed pilot PV module. In addition, as K_v is used as the output variable instead of V_{MPP} and I_{MPP}, it does not vary much

Table 4
Comparison with similar studies.

References	Method		Evaluation criteria		
	MPPT algorithm	Decision variable	Efficiency (%)	Tracking speed (s)	Oscillations
Malathy and Ramaprabha (2013)	Lookup table	V_{MPP}	95.4	0.02	less than 2 W
Kota and Bhukya (2016)	Lookup table	V_{MPP}	95	0.01	5 W
Udavalakshmi and Sheik (2018)	Lookup table	d	95	0.01	0.02%
Sarika et al. (2020)	P&O-Lookup table	d	98	0.005	less than 2 W
Banakhr and Mosaad (2021)	HS-Lookup table	V_{MPP}	93	0.1	negligible
Hadji et al. (2018)	GA	I_{MPP}	99.9	1.01	0.1%
Senthilkumar et al. (2022)	PSO, GA, BAT, GWO	d	98	NP	NP
Hoang (2021)	PSO, DPSO, GA, HS, DE	d	100	0.2	negligible
Gonzalez-Castano et al. (2021)	ABC	V_{ref}	98.4	0.16	0.25 W
Chao and Rizal (2021)	hybrid GA-ACO	d	99.9	0.18	negligible
Yousri et al. (2019)	CFPA	d	99.8	1.2	negligible
Mirza et al. (2020)	SSA	d	99.3	0.2	less than 1 W
Taherkhani et al. (2021)	FOA	d	99.8	0.13	low
Moghassemi et al. (2022)	WOADE, IWOADE	d	99.91	0.25	negligible
Motamarri et al. (2021)	MGWO	d	99.35	1	low
Eltamaly et al. (2020)	Adaptive PSO	d	99.5	3	medium
Tey et al. (2018)	DE	d	99	2	large at the start
Shams et al. (2020)	BOA	d	99.87	0.72	medium
Fares et al. (2021)	SSA	d	99.48	0.66	large at the start
Proposed technique	GA	K_v	99.96	0.07	negligible

Key: ABC: Artificial Bee Colony, ACO: Ant Colony Optimization, BOA: Butterfly Optimization Algorithm, CFPA: Chaotic Flower Pollination Algorithm, d: duty cycle, DE: Differential Evolution, DPSO: Differential Particle Swarm Optimization, FOA: Flower Optimization Algorithm, GA: Genetic Algorithm, HS: Harmony Search, I_{MPP}: Current at maximum power point (A), IWOADE: Improved Whale Optimization and Differential Evolution, MGWO: Modified Grey Wolf Optimization, NP: Not Provided, PSO: Particle Swarm Optimization, SSA: Salp Swarm Optimization, V_{MPP}: Voltage at maximum power point (V), WOADE: Whale Optimization and Differential Evolution.

with the change in environmental conditions and thus requires less memory to build the lookup table as compared to other approaches.

In Hadji et al. (2018), although GA based MPPT algorithm is used, there are significant differences in the methodology and outcomes compared to the one proposed in this paper. The first difference is the decision variable to be optimized. In Hadji et al. (2018), GA is utilized to find the optimal current at maximum power point (I_{MPP}) such that the PV power is maximized, which requires two pilot PV modules for the continuous measurement of V_{oc} and I_{sc}. On the other hand, in the proposed technique, K_v is selected as the decision variable, and only one pilot PV module is needed for V_{oc} measurement. The benefit of using K_v as a decision variable appears in the tracking speed that is around 0.07s and is almost 10 times less than the tracking speed (1.01s) reported in Hadji et al. (2018). This can be attributed to the constrained search space for K_v (0.7–0.9), which leads to faster convergence and use of a lookup table, which instantly outputs optimal K_v, whilst in the case of I_{MPP}, the algorithm has to scan the whole I–V characteristic curves for locating the MPP. Additionally, as I_{MPP} varies significantly with the irradiance conditions, it needs to be relocated every time the change in environmental condition occurs by measuring new V_{oc} and I_{sc} values. These above statements also hold true for most of the other studies mentioned in Table 4, which use the duty cycle (d) of the DC/DC converter as a decision variable, which usually ranges between 0–1. Another difference between the current study and Hadji et al. (2018) lies in calculating the PV power output. In Hadji et al. (2018), the shunt resistance (R_{sh}) in the solar PV model was ignored, which does not accurately represent the behaviour of a solar cell (Ishaque et al., 2011). In contrast, this study involves a more accurate PV model available in MATLAB/Simulink that accounts for both series resistance as well as shunt resistance. Moreover, in Hadji et al. (2018), no stopping criteria were specified for GA termination. Instead, GA was coded to be terminated after fixed number of iterations (50), which may cause inefficient convergence speed. Additionally, the performance of the proposed MPPT technique in Hadji et al. (2018) was also not tested against different irradiance profiles.

In Gonzalez-Castano et al. (2021), an Artificial Bee Colony (ABC) based MPPT algorithm was proposed with an outstanding tracking speed of 0.16s and minimal steady-state oscillations. Nonetheless, the proposed algorithm was not tested for partial shading conditions and the maximum MPPT efficiency achieved was only 98.4%. In Tey et al. (2018), Shams et al. (2020), Fares et al. (2021), improved metaheuristic optimization algorithms are proposed for tracking the GMPP during partial shading. However, these techniques exhibit large power oscillations at the beginning due to the stochastic search process and are challenging to implement. Moreover, these techniques were specifically developed to handle the partial shading conditions and treat the uniform irradiance as partial shading, resulting in slow tracking speed. Authors in Hoang (2021), Chao and Rizal (2021), Yousri et al. (2019), Mirza et al. (2020), Taherkhani et al. (2021), Moghassemi et al. (2022), Motamarri et al. (2021) have reported excellent performance for their proposed hybrid and modified optimization algorithms. However, these algorithms add complexity to the existing MPPT algorithm and are hard to implement. On the other hand, the proposed GA-FOCV technique in this paper is simple, easier to implement, and at the same time, offers better performance in terms of MPPT efficiency (99.96%), tracking speed (0.07s) with almost negligible steady-state oscillations.

4. Conclusion

In this work, a GA based MPPT technique is proposed to improve the efficiency of the conventional FOCV technique. The FOCV method stands out from the other MPPT techniques by its simple operation, easy implementation, and cost-effectiveness, as it requires only one voltage sensor to perform the MPPT. However, the low tracking efficiency is one of its major disadvantages. To overcome this, GA is utilized to find the optimal fractional constant (K_v) for the given environmental condition, which is assumed to be constant in the conventional FOCV. MATLAB/Simulink is used to investigate the performance of the proposed approach under different irradiance profiles, and the results are compared with the most commonly used P&O, IC, and hybrid MPPT techniques. The main findings of this work are:

- The tracking efficiency of the conventional FOCV technique (assuming constant K_v) varies with the environmental conditions and typically improves at high irradiance levels.

However, analyses found that assuming a constant K_v might be a simple approach but can incur significant power loss. Nonetheless, an optimal K_v value exists for the given environmental condition at which maximum PV power can be achieved. The proposed hybrid GA-FOCV technique uses optimal K_v value and significantly enhances the MPPT efficiency of the conventional FOCV by almost 3% and can track true MPP under varying environmental conditions with an average accuracy of above 99.96% .

- In comparison with other conventional techniques, including P&O and IC, the proposed GA-FOCV approach outperforms in stability, dynamic response, tracking speed, and MPPT efficiency under rapidly changing environmental conditions, whilst P&O exhibits steady-state oscillations around MPP, low efficiency at poor irradiance conditions, and loses tracking direction under rapidly changing weather conditions. Likewise, IC suffers from a slow dynamic response and low efficiency and is also not fully free from oscillations.
- Testing under partial shading conditions reveals that the proposed technique can also efficiently track the global maximum power point in the presence of multiple local power peaks. However, under such conditions, the optimal K_v may not be in the normal range of 0.7–0.82, such as 0.4 in case 1 and 0.6 in case 2 of partial shading.

Future research is warranted to investigate the effects of using different DC/DC converter topologies and optimized controller parameters.

CRediT authorship contribution statement

Aakash Hassan: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Data curation. **Octavian Bass:** Supervision, Methodology, Validation, Resources, Writing – review & editing, Project administration. **Mohammad A.S. Masoum:** Supervision, Methodology, Writing – review & editing, Project administration.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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