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A Hybrid Evolutionary-Based MPPT for Photovoltaic Systems Under Partial Shading Conditions

MANSI JOISHER, DHARAMPAL SINGH, SHAMSODIN TAHERI, DIEGO R. ESPINOZA-TREJO, EDRIS POURESMAEIL, AND HAMED TAHERI

ABSTRACT
Under partial shading conditions (PSCs), photovoltaic (PV) system characteristics vary and may have multiple power peaks. Conventional maximum power point tracking (MPPT) methods are unable to track the global peak. To address these issues, this paper proposes an improved hybrid MPPT method using the conventional evolutional algorithms, i.e., Particle Swarm Optimization (PSO) and Differential Evaluation (DE). The main feature of the proposed hybrid MPPT method is the advantage of one method compensates for shortcomings of the other method. Furthermore, the algorithm is simple and rapid. It can be easily implemented on a low-cost microcontroller. To evaluate the performance of the proposed method, MATLAB simulations are carried out under different PSCs. Experimental verifications are conducted using a boost converter setup, an ET-M53695 panel and a TMS320F28335 DSP. Finally, the simulation and hardware results are compared to those from the PSO and DE methods. The superiority of the hybrid method over PSO and DE methods is highlighted through the results.

INDEX TERMS
Photovoltaic systems, maximum power point tracking, partial shading condition, particle swarm optimization, differential evaluation.

I. INTRODUCTION
In recent years, photovoltaic (PV) systems integrated into power grids have been gaining popularity as one of the most promising and reliable energies among existing renewable energy sources. PV sources offers several advantages in terms of being clean, renewable and low maintenance. However, the low efficiency of PV systems often due to their nonlinear electrical characteristic and variable atmospheric conditions remains a challenge. Therefore, in order to overcome this main drawback a PV system needs to operate at its maximum power point (MPP). The efficiency of PV systems is considerably affected by local atmospheric conditions such as moving clouds, dust, neighbouring buildings and trees.

Due to these barriers, PV systems generate lower power [1]. More importantly, PV systems show a lower performance when the solar irradiance is not uniformly distributed over the PV array surface, known as partial shading phenomenon [2]. The latter changes the power-voltage (P-V) characteristics of PV systems by generating multiple local power maxima. It remains a challenge of global optimization to ensure that PV systems operate at their global maximum power point (GMPP) rather than at the local ones [3], [4]. Over recent years, several maximum power point tracking (MPPT) techniques in combination with power electronic devices have been proposed to deliver maximum power from the PV array. These techniques vary in some general parameters such as complexity, accuracy, cost and speed. Among these, Hill climbing (HC) [5] and perturb and observe (P&O) [6] are the most common used algorithms due to the ease of
implementation and their simple control mechanisms. These two algorithms showed a similar fundamental approach to achieve the MPP. The HC algorithm operates by periodically perturbing the duty cycle for a power converter, and the P&O algorithm works with a perturbation in the operating voltage of the PV system. The output power is a determining factor in increasing or decreasing control parameters (voltage or duty cycle) to reach the MPP. Despite of simplicity in operation of these algorithms, the steady state system oscillates around the MPP. The selection of a small step size of the perturbation can improve the oscillations while it decreases the speed of the system. Some improved P&O techniques have been proposed to overcome these drawbacks through variable perturbation step size [7], [8]. However, the major drawback of these algorithms is that they are unable to find the global peak (GP) under partial shading conditions (PSCs).

The Incremental Conductance (IC) is another commonly used MPPT technique [9], [10]. The MPP is reached when the slope of the PV power curve is zero. Similar to the P&O method, the IC suffers from a trade-off between the accuracy and speed of the system to reach the MPP, as well as incapability in tracking the GP under PSCs.

Fractional open-circuit voltage (FOCV) [11] and Fractional short-circuit current (FSCC) [12] algorithms have been found simple methods to track the MPP of a PV system. The FOCV is based on a linear relationship between open-circuit voltage and the MPP voltage. In the same way, the FSCC is presented as a ratio of short-circuit current to the MPP current. Due to the approximate aforementioned relationships, the PV system cannot find a true MPP to operate. In spite of the above-mentioned techniques, several methods such as Ripple Correlation Control (RCC) [13], the slide mode control [14], [15] and dP/dV feedback control [16] have been also proposed to achieve the MPP of the PV array. These methods often fail to track the GP under nonuniform insolation as the electrical characteristics of PV exhibit multiple peaks.

In order to improve the above-mentioned drawbacks, several methods in the family of soft computing (SC) techniques such as artificial intelligence approach and evolutionary algorithms have been attracting considerable interests recently. In the field of artificial intelligence techniques, fuzzy logic controllers (FLC) [17], [18], artificial neural network (NN) [19], [20] methods have shown effective solution in dealing with the nonlinear characteristics of the current-voltage (I-V) curve, in particular, under PSCs. However, they require extensive computation.

The evolutionary algorithm (EA) technique as a stochastic optimization method appears to be very efficient in tracking the MPP. The EA is able to find the GP regardless of isolation pattern as it is based on search optimization. Among various EA techniques, differential evolution (DE) and particle swarm optimization (PSO) has been gaining popularity in tracking the MPP under PSCs. Several MPPT algorithms based on PSO and DE techniques have been presented to date to recognize the GP among multiple local peaks. The DE offers several advantages as it is able to find the GP, it has rapid convergence and it needs few control parameters [21], [22]. However, in DE particles compete for survival while the winners hardly retain enough history. Moreover, there is no cooperation among particles to find the GP consequently, an increase in the time computation is probable. PSO is a population-based search method, which searches the MPP through a swarm of particles where each particle is considered as a candidate solution. The particles in PSO cooperate to find the global best position [23]. The PSO method requires no gradient information of function to be optimized. It has a simple, effective and fast metaheuristic approach to find the GP under PSCs. However, several improvements have been made to the conventional PSO technique to enhance its efficiency. In [24] similar to HC, the improved PSO works with direct duty cycle with a faster tracking speed and low oscillations at the MPP under PSCs. The method presented in [25] is a system-independent MPPT algorithm which sorts the obtained particle positions to avoid a large voltage stress on the power switch due to the sudden change of duty cycle. The authors in [26] proposed a deterministic PSO-based MPPT under PSCs. The control structure of this MPPT can be simplified since the random number in the acceleration factor of the conventional PSO is removed. However, two separated flowcharts are implemented to determine the local and global modes compared to the conventional PSO with a unique algorithm. A hybrid method, which combines P&O and PSO is proposed in to track the MPP in two stages [27]. In the first stage, the P&O method is employed to search for the first local maximum power point (LMPP) and then in the second stage, the PSO is used to search for the GMPP. The time chosen to apply the associated algorithm is a determining factor, in particular, when the partial shading occurs. Despite the remarkable accuracy of the above-mentioned PSO methods compared to the conventional one under PSCs, the time required for convergence is still long. In PSO each particle is influenced by its personal best performance and that achieved by the best particle in its neighborhood throughout its lifetime. However, the particles in PSO are not eliminated when they meet a new worth position. Thus, longer computation time for large search space, particularly under various partial shading is inevitable. Another issue regarding the PSO technique is that it can be trapped at the local peak in a high-dimensional space and has a low convergence rate [28]–[30]. To overcome these main drawbacks, this paper proposes an improved MPPT method based on a synergism of PSO and DE, called the PSO-DV algorithm. In the PSO-DV, the mutation and crossover processes in DE method are used to generate a trial vector. Then, using merit criterion, unlike the PSO, the particle is moved to the new position only if this location meets a better fitness value. Hence, the computation time could be greatly reduced, in particular, under PSCs. Moreover, to avoid the particles from being trapped at one of the local peaks, a condition is used in the proposed algorithm. The particle escapes from the LMPP by a random mutation and keeps the swarm moving. In fact, the proposed PSO-DV MPPT i) benefits from features of PSO and DE for searching
the GP under PSCs, ii) decreases greatly the computation time, and iii) copes with dynamic change in irradiance levels under large fluctuations of insolation.

The rest of the paper is organized as follows. An overview of PSO and DE algorithms is presented in Section II. The synergy of PSO and DE is developed in Section III. The theory of the PSO-DV is implemented in Section IV. The simulation verification is presented in Section V. The experimental results are illustrated in Section VI. Finally, the concluding remarks are presented in Section VII.

II. OVERVIEW OF PSO AND DE ALGORITHMS

PSO and DE algorithms have been known as popular techniques of EA. Recently, these techniques have been gaining much attention due to their ability in optimizing real-valued nonlinear and multi-modal objective functions. These techniques are based on search optimization, the GP could be tracked with a reasonable convergence time and a better dynamic response than the conventional methods.

A. 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 [31]. 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. The movement of each particle around in the search space is controlled by its own best position and the globally best position found by the entire particles so far. The position and velocity of the ith particle in the swarm are determined as follows:

\[
x_{i}^{k+1} = x_{i}^{k} + v_{i}^{k+1}
\]
\[
v_{i}^{k+1} = \omega v_{i}^{k} + c_{1} r_{1}(p_{besti} - x_{i}^{k}) + c_{2} r_{2}(gbest - x_{i}^{k})
\]

where \(x_{i}^{k}\) is the position of individual i at iteration k, \(v_{i}^{k}\) is the velocity of individual i at iteration k, \(\omega\) is the inertia weight, \(c_{1}\) and \(c_{2}\) are the acceleration coefficients, \(r_{1}\) and \(r_{2}\) are the random positive numbers between 0 and 1, \(p_{besti}\) is the personal best position of individual i and \(gbest\) represents the global best position found so far in the community.

B. PSO ALGORITHM

DE, which is a member of the genetic algorithm (GE), was introduced by Storn and Price in 1995 [32]. The DE is known as a stochastic, population-based optimization algorithm. The DE technique starts with the initialization of a random population and then the mutation operation is applied on the individuals of the current population, called target vectors, to produce a mutated vector. Then, the crossover operation generates a new vector (trial vector). The trial vector can replace the target vector in the next iteration if the trial vector acquires a better fitness value than the target vector. The optimization process of DE could be presented briefly as follows:

Step 1: Initialization

The optimization process of DE starts through an initial population of D-dimensional parameter vectors \(x_{i}^{G} = [x_{i1}^{G}, x_{i2}^{G}, \ldots x_{iD}^{G}]\). Individuals \(x_{i}^{G}\) are initialized randomly in the certain range with a lower and upper limit, \(x_{L}\) and \(x_{H}\) as follows:

\[
x_{i}^{1} = x_{L} + \text{rand}[0, 1](x_{H} - x_{L})
\]

where \(x_{L} = [x_{L1}, x_{L2}, \ldots x_{LD}]\) and \(x_{H} = [x_{H1}, x_{H2}, \ldots x_{HD}]\).

Step 2: Mutation

In order to generate a donor vector \(v_{i}^{G}\), mutation process should be applied to each parameter vector \(x_{i}^{G}\) in the way that, three vectors \((x_{i1}^{G}, x_{i2}^{G}, x_{i3}^{G})\) are randomly selected in the range \([1, NP]\) where NP is the population size. It should be mentioned that the indices \(i, r_{1}, r_{2}\) and \(r_{3}\) are distinct. The mutated vector \(v_{i}^{G}\) is generated by adding the weighted difference between two vectors, randomly chosen, to a third vector as follows:

\[
v_{i}^{G} = x_{r_{1}}^{G} + F(x_{r_{2}}^{G} - x_{r_{3}}^{G})
\]

where \(F\) is a mutation scaling factor that scales the difference of two vectors, which is usually selected between 0 and 1.

Step 3: Crossover

The crossover operation involves generating a trail vector, \(u_{i}^{G} = [u_{i1}^{G}, u_{i2}^{G}, \ldots u_{iD}^{G}]\) through mixing the target vector \(x_{i}^{G}\) with the mutated vector \(v_{i}^{G}\). The DE uses commonly two kinds of crossover schemes, i.e., binomial and exponential [32]. The binomial crossover method, used in this work, yields the following condition to produce the trail vector:

\[
u_{j,i}^{G} = \begin{cases} v_{j,i}^{G} & \text{if rand}(0, 1) < CR \\ x_{j}^{G} & \text{otherwise} \end{cases}
\]

where \(CR\) is known as crossover constant, similar to \(F\), is a control parameter of DE.

Step 4: Evaluation and Selection

An important point that should be taken into account in DE method is to keep the population size constant during the operation. The DE method involves competing between the target and trial vectors to take the place for the next generation. In fact, the trial vector will replace the target vector (parent vector) if it achieves the best fitness value, otherwise the target vector remains in the population. Hence, it ensures that the population either gets better fitness value or continues with the same target vector, but never deteriorates. The selection stage can be expressed by the following condition that the objective function \(f(x)\) requires to be minimized.

\[
x_{j}^{G+1} = \begin{cases} u_{j}^{G} & \text{if } f(u_{j}^{G}) < f(x_{j}^{G}) \\ x_{j}^{G} & \text{otherwise} \end{cases}
\]

III. SYNERGISM OF PSO AND DE

As mentioned, the main feature of the PSO is the cooperation among the population individuals. In fact, each individual
determines its destination based on its personal best experience and that globally achieved in the population. In PSO algorithm, the values of \( r_1, r_2 \) and \( \omega \) can affect the direction of a particle to the MPP as they conduct a particle toward the direction of \( p_{\text{best}_i} \) and its previous direction. Since the values of \( r_1 \) and \( r_2 \) are random, distributed within [0,1], the next position of the particle might not be better than the \( p_{\text{best}_i} \) (Fig. 1). Moreover, in PSO the particles are not eliminated even when they experience the worst fitness. Thus, since the particles remain in the memory of PSO, it wastes the limited computational resources, consequently a slower speed in convergence. On the other hand, the DE algorithm employ selection and mutation operators to forces the individual agent to find a better fitness value to survive in the next generation. The main characteristic of DE is to keep the competition in the population while the winning particles hardly keep sufficient history. Therefore, the advantage of one method can compensate for the shortcomings of the other technique. Hence, a new algorithm was developed based on a synergy of PSO and DE, called PSO-DV [33].

In order to circumvent the above-mentioned weakness of each method, a differential operator, borrowed from DE, in the mutation stage is coupled with the velocity update scheme in PSO. The operator is invoked on the position vectors of two randomly chosen individuals, different from their best fitness.

Thus, in the new algorithm, individuals are prohibited from circulating in the useless regions of the search space. Similar to what we have in the DE, for a given particle \( i \), two random distinct particles \( j \) and \( k \) are selected. Hence, a difference vector \( \bar{y} \) can be defined as follows:

\[
\bar{y} = \bar{x}_k - \bar{x}_j
\]

Then, the velocity vector in (2) is modified and then presented in the selection condition as follows:

\[
v^{k+1}_i = \begin{cases} 
\omega v^k_i + \alpha (p_{\text{best}_i} - x^k_i) & \text{if rand}(0,1) < CR \\
v^k_i & \text{otherwise}
\end{cases}
\]

where CR is a random value in (0,1).

Thus, it can be seen that the velocity vector created by the personal best experience is replaced with differential vector borrowed from the DE method.

According to the obtained velocity vector, \( v^{k+1}_i \) a new trial position \( T_i \) is generated as follows:

\[
T_i = x^k_i + v^{k+1}_i
\]

To select the next position of each particle the following condition with the objective function \( f(x) \) is proposed.

\[
x^{k+1}_i = \begin{cases} 
T_i & \text{if } f(T_i) < f(x^k_i) \\
x^k_i & \text{otherwise}
\end{cases}
\]

Therefore, for each irritation, the new velocity is determined and the particle either reaches a better position in the search space or keeps its previous location. Thus, the current position of the particles is the best ones that they have ever experienced. Hence, the term \( (p_{\text{best}_i} - x^k_i) \) in PSO is eliminated. Fig. 2 shows the typical movement of a particle in the PSO-DV. As observed from Fig. 2, the vector \( p_{\text{best}_i} - x^k_i \) is eliminated as the actual position of the particle is its personal best fitness value.

Sometimes for a number of iterations, a particle may get stagnant at any point the search space (locals) as follows:

\[
x^{i+K}_i = x^{2+K}_i = x^{3+K}_i \ldots = x^{K+N}_i
\]

To avoid this problem, the particle is shifted by a random mutation to a new location through the following equation.

\[
x^{k+N+1}_i = x^{\text{min}}_i + \text{rand}(0,1)(x^{\text{max}}_i - x^{\text{min}}_i)
\]

where \( x^{\text{max}}_i \) and \( x^{\text{min}}_i \) are the permissible bounds of the search area and \( N \) is the maximum iteration number.

The new algorithm offers both respective cooperative and competitive features of PSO and DE. In the PSO-DV the promising individuals share their experiences, which leads to a faster convergence. Moreover, worse individuals far away from the global optima are prohibited to participate in the next irritation. In this way, the search area becomes more concentrated, close to the global optima leading in saving the computational time. Furthermore, the mutation operator incorporates to PSO to increase diversity of the population that enables the particles to escape from local trap.

**IV. IMPLEMENTATION OF PSO-DV TO MPPT**

The proposed PSO-DV described in the previous section is applied to the MPPT algorithm to track the MPP, in particular, under PSCs. To evaluate the effectiveness of proposed PSO-DV algorithm, a simple block diagram (Fig. 3)
consisting of a PV panel, a DC-DC converter, a load and a controller in which the proposed MPPT technique is implemented is presented. The MPPT controls the converter operation through the duty cycle varied by measured voltage and current at the final output. This circuit simplification reduces the cost and complexity of the system rather than where individual MPPT along with associated voltage and current sensors, located at the output of each panel. In order to implement the PSO-DV method into the MPPT algorithm, the duty cycles $d_i$ with a population consisting of $N_p$ individuals are defined.

$$x^k_i = d^k_i = [d_1, d_2, d_3, \ldots , d_{NP}]$$

(13)

Moreover, the following objective function is defined.

$$P(d^k_i) > P(d^{k-1}_i)$$

(14)

The PSO-DV algorithm is based on the PSO that the velocity vector is perturbed by the mutation process, borrowed from DE. Fig. 4 shows the flowchart of the proposed PSO-DV MPPT that includes the following general steps:

**Step 1: Parameters values selection**

The values of required parameters in the PSO-DV including population size, maximum irradiation, learning factor and inertia weight are selected.

**Step 2: Particles initialization**

The particles can be initialized on a fixed position in the range of $d_{\text{min}}$ to $d_{\text{max}}$ that $d_{\text{min}}$ and $d_{\text{max}}$ are the respective maximum and minimum duty cycles. Empirical observation has shown that the MPP on the P-V curve occurs at 80% of the open voltage of the PV module.

**Step 3: Fitness evaluation**

The particle $i$, which is the output of digital controller, controls the output voltage and current through the PWM command. The fitness value $P_{PV}$ of each particle (duty cycle) then can be determined through the measured voltage and current.

**Step 4: Update personal and global best positions**

According to (10), the current position of the particle in PSO-DV method is the best position it has ever experienced. Thus, in this step, the best fitness value of the particles in the community for each irradiation is selected.

Step 5: Velocity calculation of particles by differential operator

When the fitness values of particles are determined, the updated velocity of particles should be determined by three terms, generated by the velocity of the particle, the mutation process (borrowed from the DE algorithm), and the information obtained from the global best position. Equations (8-10) are represented in terms of duty cycle as the position of each particle as follows:

$$ v_{i}^{k+1} = \begin{cases} \omega v_{i}^{k} + \alpha y + c_2 r_2 (g_{\text{best}} - d_{i}^{k}) & \text{if rand (0, 1) < CR} \\ v_{i}^{k} & \text{otherwise} \end{cases}$$

(15)

$$ T_i = d_i^{k} + v_{i}^{k+1} $$

(16)

$$ d_{i}^{k+1} = \begin{cases} T_i & \text{if } f(T_i) < f(d_{i}^{k}) \\ d_{i}^{k} & \text{otherwise} \end{cases} $$

(17)

**Step 6: Escape from local peaks**

If the particle (duty cycle) oscillates around a point for a number of iterations, the particle can escape from the LMPP...
by a random mutation as follows:
\[
d_{1}^{1+K} = d_{1}^{2+K} = d_{1}^{3+K} \ldots = d_{1}^{K+N} = d_{1}^{K+N}
\]
(18)

\[
d_{1}^{k+1} = d_{\text{min}} + \text{rand}[0, 1](d_{\text{max}} - d_{\text{min}})
\]
(19)

where \(N\) is the maximum number of iterations.

**Step 7: Convergence detection**

The PSO-DV will stop if the maximum number of irritations is reached. Thus, the obtained position is gbest.

**Step 8: Partial shading verification**

The operating point (gbest) obtained by the MPPT changes with environmental conditions as well as the load connected across the panel. In such conditions, the new or initialized particles should start searching the MPP. Thus, the algorithm is reinitialized whenever the following condition is satisfied.

\[
|P_{\text{pv,new}} - P_{\text{pv, last}}| \geq \Delta P(\%)
\]
(20)

where \(P_{\text{pv, last}}\) is the power at the MPP of the last operating point.

The proposed PSO-DV reduces the computational time rather than the conventional PSO as the instant value of each particle (duty cycle) is the best one that it has had so far. Thus, unlike the conventional PSO, the PSO-VD prohibits the particles from visiting the unnecessary positions by the differential operator borrowed from the DE. In addition, in order to avoid from oscillating around a local optimum, an online verification condition is added to the conventional PSO. The particle can be shifted to a new location by a random mutation when it gets stagnant at local optima.

**V. SIMULATION VERIFICATION**

To verify the correctness of the proposed method, simulation analysis is conducted using MATLAB/SIMULINK. Fig. 5 illustrates the schematic of the PV system used in this study. This consists of a DC-DC boost converter, a PV array, a battery pack and the MPPT controller. The converter is designed for continuous inductor current mode. The key specifications of the converter and PV module are shown in Table 1 and Table 2.

| Parameter            | Value     |
|----------------------|-----------|
| \(C_{\text{m}}\)     | 10 \(\mu\)F |
| \(C\)                | 210 \(\mu\)F |
| \(L\)                | 2 mH      |
| Switching frequency  | 20 kHz    |

In order to justify the proposed PSO-DV method, three partial shading cases are examined. The results are compared with the conventional PSO and DE methods. Fig. 6 represents the corresponding I-V and P-V curves for Case 1. Out of the 3 PV panels under investigation, 2 panels were shaded in this case. This results in 2 peak values in which the leftmost peak is the GP. The maximum power is 22.17W at 17.26 V.

The proposed algorithm PSO-DV stabilizes at the GP in 1 second. Given that there is only a single local peak for the output curve, with a considerable difference between GMPP and LMPP, it is easier to track this GMPP through PSO method with a proper initialization of particles. By contrast, the initialization is completely random in DE and hence can be used to evaluate all ranges of search space but the search quality is degraded in this case. For this case, results prove that the proposed algorithm is able to track the GMPP faster than the DE and PSO algorithms. The proposed algorithm experiences less power oscillations.

Fig. 8 represents the characteristic curves for Case 2. In this particular case, all the 3 PV panels are partially shaded to a certain degree. This results in 3 peaks in the P-V curve, the maximum power, in this case, is 135W at 37V. The local peaks are located at 126W and 88W respectively.

This condition differs from the previous condition as the difference between GMPP and one of the LMPP is lesser, which makes it difficult for the conventional techniques to track the GMPP. In the PSO algorithm as
the iterations increase, the search space is narrowed down. Hence, the particles get trapped at the local peaks as already stated in [28]–[30]. It can be seen from the PSO simulation result, the particles are stuck at the local peak at 125 W. However, the conventional PSO algorithm can be used in this case by initializing the particle near the MPP. This makes the algorithm-specific to a particular condition and hence, will fail to track GMPP in other PSCs.

On the other hand, DE algorithm is able to track the GMPP in this case but the results prove the proposed algorithm PSO-DV reached the GMPP faster. However, the proposed algorithm PSO-DV uses a random mutation loop to escape local peaks. Hence, it experiences power oscillation. The proposed method is able to achieve the MPP faster compared to other methods.

Case 3 is demonstrated in Fig. 10, there are 3 peak values for the output curve, the GP is located at the rightmost peak, 92 W. The middle peak, a local peak is at 80 W. The difference between the middle local peak and the GP is less and hence the conventional techniques get trapped at this local peak. It is verified from the simulation results that particles in PSO are not able to escape local peaks. PSO algorithm can be used to track GMPP in this case by setting some limitations on the searching area or moving direction, which reduces the searching time as well as high-tracking efficiency. However, the PSO method loses its randomness and then loses its inherent advantages. Similar to the previous case the DE algorithm is able to track the GMPP but the performance is very poor. The proposed algorithm is able to escape local peaks due to random mutation. However, the result of the proposed algorithm shows that it evaluates all ranges of search space faster than PSO and DE algorithms.
VI. EXPERIMENTAL VALIDATION

The experimental tests were conducted using a PV array consisting of two series-connected ET-M53695 PV modules as shown in Fig. 12. The electrical parameters of ET-M53695 Panel at STC are listed in Table 3. The terminal voltage of the PV array is controlled by duty cycle of the IGBT switch of the boost converter to achieve the MPP. The PV array is connected to a load via the boost converter. The parameters of the experimental setup are listed in Table 4. A voltage sensor and a current sensor are used to measure the PV array voltage and current. The algorithms are implemented using the Texas Instruments TMS320F28335 DSP. The platform for software development is the Code Composer Studio (CCS 8.1.0). The control programs were developed in C environment.

The enhanced ePWM1 module of DSP is used as the internal clock base for the sampling frequency. The timer interrupt frequency determines how often the duty cycle of the PWM signal is updated. The timer interrupt frequency is kept at 10 Hz or every 100 ms. The selection of this frequency depends on the time constant of the specific PV system. In fact, the PV system should reach a steady-state operation before another MPPT cycle begins. The timer interrupt frequency is critical as it determines the update frequency of the MPPT. It must also ensure that the code does not overrun and cause unpredictable behaviour. Natural PSCs often occurred as a result of the shadow of a nearby building. Artificial PSCs were also created using plastic sheets with different transparencies. The PV characteristics were monitored using HT Instruments I-V 400W PV Panel Analyzer and irradiance meter test kit. Similar to the simulation section, three algorithms of PSO, DE and the proposed DV-PSO are experimentally tested for different scenarios of PSCs and the power graphs approaching the MPP are captured on code composer studio as follows. For Case 1, as shown in Fig. 13, there are 2 peaks in the P-V curve and the leftmost peak is the global maxima, at 11 W whereas the local peak is at 5.6 W. Fig 14. illustrates the experimental results for Case1. It is observed that the PSO and DE algorithms are stuck at the local maxima of 5W, whereas the proposed algorithm PSO- DV is able to reach the global maxima at 11 W, 7.7V.

The proposed algorithm is able to escape all the local peaks due to the random mutation condition. Whenever the number of iterations is equal to the maximum number of iterations and the particle is oscillating around a particle position,
the random mutation loop is initialized. Hence, in this case, the proposed algorithm faces more power oscillations before stabilizing at a global peak.

Case 2 is shown in Fig. 15, there are 3 peaks in the P-V curve of the system. The middle peak is the global maxima at 20W. The difference between the voltage at global maxima and local maxima is considerable and hence this is an easy situation for both PSO and DE techniques. It is observed from the hardware verification results shown in Fig. 16. PSO algorithm is easily able to reach the GP as the initialization of particles was set in this particular way. DE is able to escape the local peaks and reach global maxima initially but later is stuck at an untrue point at 17 W. The proposed algorithm DV-PSO is able to track the GMPP as fast as the PSO algorithm, and unlike PSO it is not a case-specific algorithm. However, after every 40 samples, the algorithm experiences random mutation to ensure particles are not stuck at a local peak.

To ensure a stable graph, once the particles have reached a global peak, the maximum number of iterations can be set to 1000 and the random mutation loop can be accordingly modified.

Case 3 demonstrated in Fig. 17 is different from the previous case as the difference between the power at the GP and the local peak is less. This makes it difficult for conventional techniques to track the GP. On careful observation, it is noted...
that the right-hand side peak is the global maxima at around 14 W, 30 V. The leftmost peak is a local peak at around 13.5 W, 16 V.

Fig. 18 represent the hardware verification results for Case 3. It is observed from the results that power for all the algorithms is almost the same around 13.5W. However, the voltage is in the case of PSO and DE algorithms are 16.05 V and 17.7 V respectively. The voltage of the PV system in PSO-DV algorithm is 26.8 V. This proves that the first 2 algorithms are stuck at the left-hand side peak which is a local peak. The proposed algorithm is able to approach the global maxima faster than conventional methods. The algorithm experience power oscillation after every 40 samples due to the random mutation loop. This can be adjusted by changing the maximum number of iterations. As explained earlier this is the reason, PSO-DV algorithm is able to escape all the local peaks in every situation.

VII. CONCLUSION

This paper is a continuation of usage of computational algorithms to find the GP of PV systems under PSCs. A high-performance MPPT hybrid algorithm based on PSO and DE algorithms is proposed. Through a sequential mathematical overview of PSO and DE algorithms, a hybrid algorithm PSO-DV is proposed. The main features of PSO and DE are combined to overcome their drawbacks. The proposed hybrid MPPT uses a random mutation loop to escape from all the local peaks. The triggering of this loop depends upon the maximum number of iterations. The performance of the hybrid MPPT is verified using both simulation and hardware setup. The proposed methodology is tested for 3 different PSCs. The proposed algorithm is an advancement in this field that makes the system more robust and improves the overall computational speed. Contrary to the conventional PSO and DE techniques, it can find the true GMPP. This algorithm successfully copes with dynamic change in irradiance levels and is applicable for real-time conditions.

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