

Differential Evolution Based Solar Photovoltaic Array Reconfiguration Algorithm for Optimal Energy Extraction during Partial Shading Condition

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ABSTRACT

To increase energy yield from an installed photovoltaic (PV) array, particularly during partial shading condition (PSC), a new technique based on reconfigurable PV array interconnection is proposed in this work. The proposed technique works by dynamically changing the interconnection of PV modules to form a new configuration using a switching matrix inside the array. The criteria of good reconfigurable PV array interconnection techniques depend on the efficiency and accuracy of the control algorithm to optimally reconfigure the PV array to maximize the total output power. Hence, this paper proposes a new control algorithm using differential evolution (DE) for photovoltaic array reconfiguration (PVAR). To verify the superiority of the proposed algorithm, DE is compared with the particle swarm optimization (PSO) algorithm. Results confirm that DE performs well in terms of the amount of energy production during PSC. For all the nine shading patterns tested on a 3×3 PV array, DE yields 1% to 5% more power than PSO.

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1. INTRODUCTION

Environmental health is one of the most crucial problems the world is facing. Thus, a few environmentally friendly solutions have been proposed. A photovoltaic (PV) system is a power-generating system that produces clean energy and is in demand by many countries. Governments of different countries have formed policies and frameworks for renewable energy, especially those that use PV technology. These policies encourage the use of PV solutions instead of coal, natural gas, and petroleum, which emit greenhouse gases [1-3]. However, PV exhibits low efficiency in converting light to electrical energy due to mismatch losses. The primary reason for mismatch losses is partial shading condition (PSC) because of overhead clouds, nearby buildings, or any surrounding objects. PSC causes considerable power losses to the PV system [4-7].

Avoiding PSC, especially passing clouds, is close to impossible. Research has proposed several approaches to reduce power losses. Three major ways to mitigate power losses are as follows: (1) improved maximum power point tracking techniques, (2) modified system architectures, and (3) improvised PV array configurations [8-12]. In [13] and [14], the researchers proposed several static configurations and tested their performance. The researchers concluded that total cross-tied (TCT) configuration was the best configuration based on its performance compared with the other common configurations, such as series-parallel, bridge-

linked, and honeycomb. Power loss was reduced in the TCT configuration because of the cross-tie (C_T) that connects across each junction as an alternate path for the current to flow through the PV array.

[15] and [16] improved the PV array configuration method into the PV array reconfiguration (PVAR). PVAR forms a new configuration based on the optimal output power under static and nonstatic PSC by changing the connection or physical movement of the PV modules. Sanseverino *et al.* proposed PVAR control by switching to the matrix that is based on irradiance equalization method. This method reduced the multiple peaks of power–voltage (P – V) and current–voltage (I – V) curves caused by bypassing diodes in the PV array to a single peak. However, this method is not precise because the irradiance values of each PV module are estimated by an equation and not by an irradiance meter, which provides a high chance of obtaining accurate readings. Furthermore, implementing this method entails a high cost because current and voltage sensors are required for each PV module [17]. Babu T.S. *et al.* implemented particle swarm optimization (PSO) algorithm to control and optimize the switching matrix of PVAR with an array size of 9×9 . The objective function of the PSO algorithm is irradiance equalization, which utilizes an equation to estimate the irradiance values. Although this work used the PSO algorithm as the optimization method, the PVAR does not yield the optimal energy because the size of the array after reconfiguration is still fixed at 9×9 , and the irradiance values are not comparable with the real values [18]. Ramaprabha proposed a PSO algorithm that is also implemented in PVAR and whose objective function is power maximization. The variable of the objective function is the current value of the PV array. Nevertheless, the accuracy of the PSO algorithm in this work is not constant, and it does not optimally extract the energy [19]. Consequently, some improvements have been made in this work by utilizing differential evolution (DE) algorithm in PVAR. The PVAR works by changing the electrical connection between the PV modules regardless of its physical position. The objective function of DE in this work is similar in [19]. The objective function can be achieved by changing the switches of the modules. Only one of each current and voltage sensors is needed to measure the output power of each population during the optimization process. The proposed DE-based PVAR is compared with PSO to analyze the performance of both algorithms. Both algorithms are tested on a 3×3 PV array under 9 shading patterns by using MATLAB/Simulink® software.

2. BASIC PRINCIPLE

This work uses MATLAB/Simulink® software to develop the DE-based PVAR. To implement PVAR, a suitable model of PV cell needs to be developed in the software. Then, the PV cells are connected to form the PV modules and an array. Normally, 36 PV cells are connected in series to form a PV module. In this work, a single-diode PV model is used to model the simple yet accurate characteristics of PV cells. The single-diode model provides an excellent qualitative prediction of PS and mismatch effects [9, 20]. Figure 1 shows the equivalent circuit of the single-diode PV model.

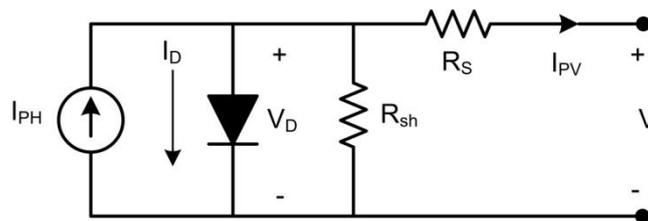


Figure 1. PV cell equivalent circuit

$$I_{PV} = I_{PH} - I_o \left[\exp \left(\frac{V_{PV} + R_s I_{PV}}{a V_T} \right) - 1 \right] - \left[\frac{(V_{PV} + I_{PV} R_s)}{R_{sh}} \right] \quad (1)$$

where I_{PH} : light-generated current,
 I_{PV} : current generated by incident light,
 I_o : reverse saturation current,
 R_s : series resistance,
 R_{sh} : parallel resistance,
 a : diode ideality constant,
 V : thermal voltage of the PV module with N_s

cells connected in the series ($N_s kT/q$)
 q : electron charge ($1.60217646 \times 10^{-19}$), and
 k : Boltzmann constant ($1.3806503 \times 10^{-23}$ J/K).

The equation for the single PV model is extracted from Equation (1). The light-generated current I_{PH} depends on the short circuit current in the standard test condition $I_{SC,STC}$, the irradiance experienced by the surface of PV module G , and the irradiance of the standard test condition G_{STC} , as stated in (2)

$$I_{PH} = (I_{SC,STC} + K_i \Delta T) \frac{G}{G_{STC}} \frac{R_{sh} + R_s}{R_{sh}} \quad (2)$$

K_i is the temperature coefficient of the short-circuit current and $\Delta T = T - T_{STC}$, where T is the surrounding temperature of the PV module. The conditions that have been set for standard test condition (STC) are $T_{STC} = 25$ °C and $G_{STC} = 1,000$ W/m². As indicated by Equation (2), the performance of PV is susceptible to the irradiance and temperature level. In the case of PSC, the observation on the irradiance and temperature levels is set constant according to STC. The parameters of the PV cell for this paper are based on the National Renewable Energy Laboratory system. This work employed 9 PV modules (API156P-230) manufactured by Advance Solar Hydro Wind Power.

PSC can cause the hotspot effect on the PV module, thereby causing the PV module to overheat and become damaged entirely. Adding a bypass diode in the anti-parallel connection with the PV module can reduce the effect, as shown in Figure 2. PV1 is the module that experiences PSC. Hence, the bypass diode creates a new path for the current produced by the non-shaded PV modules to flow across the string.

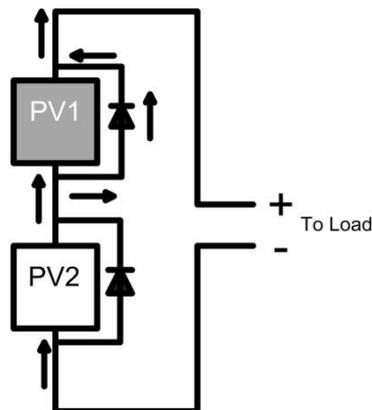


Figure 2. PV modules connected with bypass diode

3. DEVELOPMENT OF THE PV ARRAY RECONFIGURATION (PVAR)

To build a high-performance PVAR circuit, the basic topology of the circuit should be selected based on static configuration. Most researchers proved that the TCT configuration is the best static configuration under PSC with less power loss [21, 22]. Consequently, the PVAR connection in this work is developed based on a TCT topology. Each series of connected PV modules is connected with a cross-tie (CT) across each junction. Figure 3 shows the wiring diagram of PVAR that implements a switching matrix that is controlled by a digital microcontroller unit. The PV modules in the PVAR are represented by PV1 to PV9.

The green lines show the connection of the microcontroller unit to each set of the switching matrix. The microcontroller is also connected to the voltage and current sensors. Hence, the microcontroller can determine the output power of the PVAR during the reconfiguration process. Moreover, the switching matrix rearranged the electrical connection of the PV modules within three rows in the PVAR to form the new reconfiguration. The PV modules in the PVAR switched the electrical connections to the first row when the microcontroller unit set the command "1" to the switching matrix, then to the second row when the command is set to "2," and then to the third row when the command is set to "3."

Figure 4 illustrates how the switching matrix of PVAR changed the electrical connection between the PV modules. PV7 and PV9 are shaded. The initial physical positions and electrical connections of PV7

and PV9 are in the first and third rows, respectively. After the microcontroller unit set the command to the switching matrix based on the maximum output power, the electrical connections between PV7 and PV9 are changed to the second and first rows, respectively, without altering their physical positions.

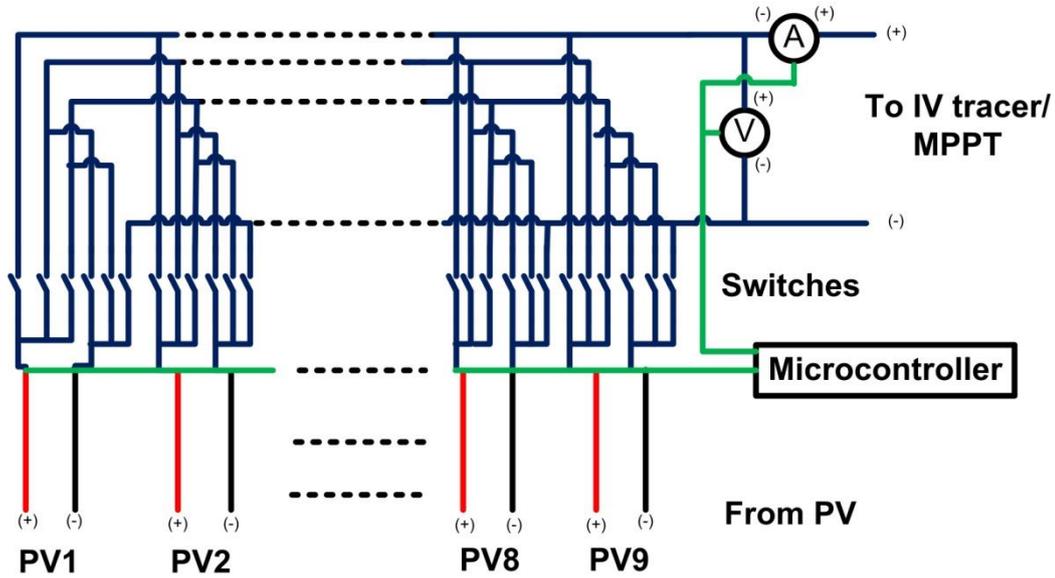


Figure 3. Wiring diagram of the PVAR circuit

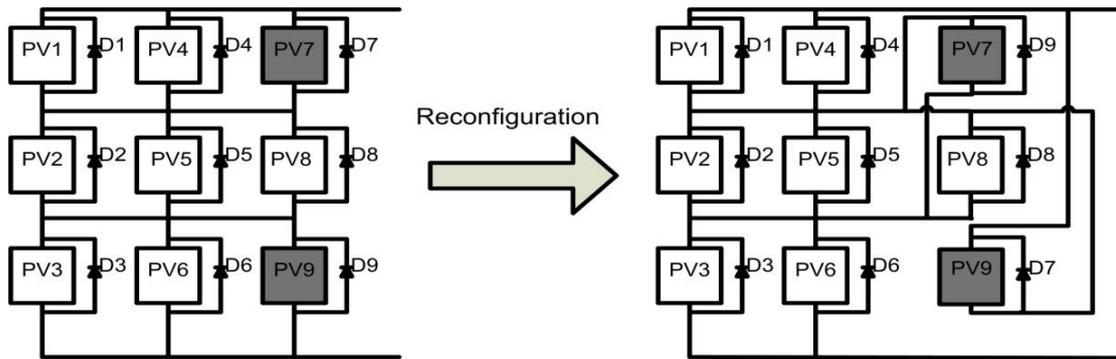


Figure 4. PVAR circuit before and after reconfiguration

4. DIFFERENTIAL EVOLUTION BASED PVAR

Solving for the switching matrix of the PV array is complicated under certain shading patterns, and several iterations are needed to obtain the result. To solve this problem and to reach the optimum power from the PV array, the DE algorithm is employed to reconfigure the switching matrix. DE was introduced in [23] and is one of the most powerful population-based optimization algorithms. DE is a simple algorithm that requires few control parameters, and it works by creating a new candidate solution under a different equation with different techniques for a problem that requires maintaining the size of a population. The new candidate and the existing solutions are compared to produce the best fitness for the objective function of the problem. The chosen solution stays in the population until the next preferred solution takes place.

This algorithm aims to optimize a problem or an objective function X. The objective function of the DE algorithm is the maximum output power of PVAR. The population P in DE has individuals of the population that are NP real-valued parameter vectors. The potential solution candidate is formed through the individuals of the population and can be described as (3)

$$P^G = X_i^G, i = 1, 2, \dots, NP, G = 1, 2, \dots, G_{max} \tag{3}$$

The DE population size is set at 10, and each individual in the population has its own dimension size, which is set to 9 because the PVAR circuit has 9 PV modules. The population works as an individual that produces the potential candidate in solving the optimization problem. Furthermore, the generation G is set at 25, wherein 10 individuals in the population will iterate 25 times. As mentioned in the previous section, the microcontroller in the PVAR circuit needs to set the commands “1,” “2,” and “3.” Therefore, the constraints set in this work are 1 for the lower boundary and 3 for the upper boundary based on Equation (4).

$$L \leq X \leq H : L, H \in R^D \tag{4}$$

Given that DE is a population-based algorithm, the initialization of the population is the first step during optimization. The initial population P^0 for the first generation of the vector is randomly generated according to Equation (5)

$$P^0 = x_{i,j}^0 = rand(0,1).(x_{j,U} - x_{j,L}) + x_{j,L} \tag{5}$$

The function of $rand(0,1)$ generates a random number within the range 0–1, where $x_{i,j}^0$ is the vector of the initial generation, i -th individual population, and j -th control variables or dimension that is generated within the constraint of upper limit $x_{j,U}$ and lower limit $x_{j,L}$.

Mutation is an important process in an evolution-based algorithm. The mutation process is illustrated in Figure 5. Mutant vector V_i^G is produced during this process to form a new candidate solution for the existing solution candidate, which is known as target vector X_i^G . Five mutation strategies can be used in DE to generate V_i^G in each generation. However, only one commonly used strategy is utilized in this work, which is shown in Equation (6), and the differential constant is set as $F = 0.9$.

$$DE/rand/1 \quad V_i^G = x_{r1}^G + F.(x_{r2}^G - x_{r3}^G) \tag{6}$$

Crossover operation is performed to shuffle the component in the mutant and target vectors, thereby producing a chosen vector that is known as trial vector U_i^G . The scheme of the crossover rate CR is set as 0.5 in this work.

Then, the trial and target vectors go through the process of choosing the vector that will survive in the next iteration. The selection is based on the maximum output power of the PVAR. After the iteration of the generation is completed, the best combination cases will be selected as the solution for the objective function. The whole process of DE-based PVAR is explained in Figure 6.

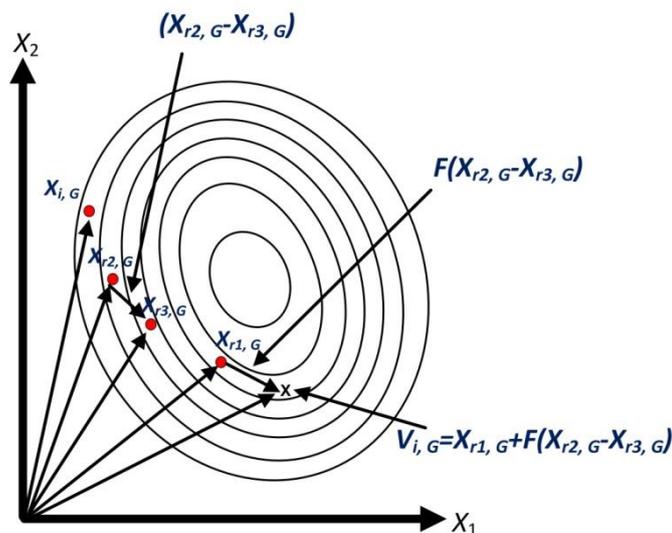


Figure 5. Illustration of DE mutant vector (DE/rand/1)

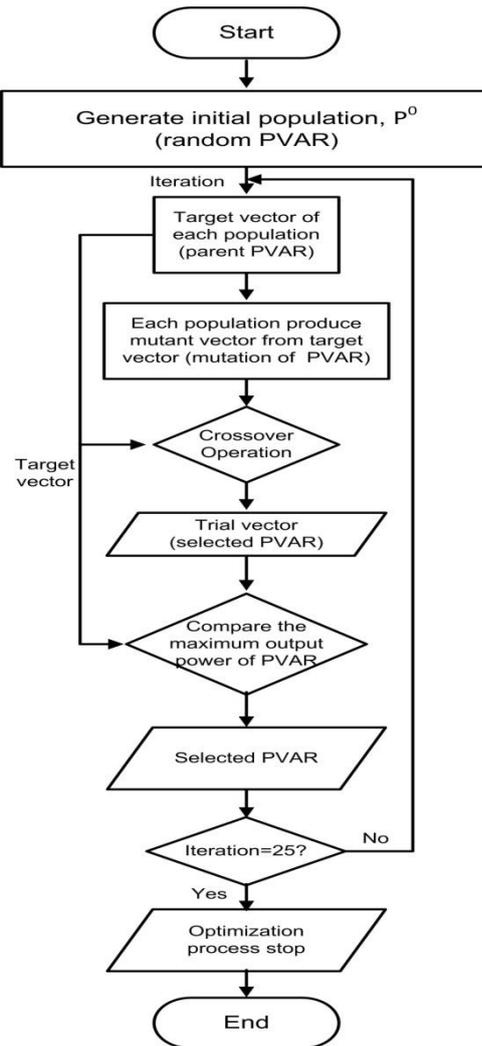


Figure 6. Flowchart of the DE optimization process

5. PERFORMANCE OF DE AND PSO BASED PVAR

In this work, the proposed DE-based PVAR is compared with the PSO algorithm to observe their effectiveness and performance. Similar to DE, PSO is a population-based algorithm. Thus, comparing both algorithms in terms of their fitness and accuracy in optimizing PVAR output power under PSC is reasonable. The population, dimension, and generation for both algorithms are set similarly. The performances of DE- and PSO-based PVAR are tested on nine shading patterns to simulate the real PSC, as shown in Figure 7. The PV modules in the PVAR are set with different irradiance values of 300, 500, 700, and 1,000 W/m². The maximum output powers of the fully irradiated patterns for both algorithms are similar. Therefore, only eight remaining patterns will be observed. Otherwise, the fully irradiated pattern becomes a reference pattern.

The performances of DE and PSO are observed based on the percentages of power losses (%PL). To analyze %PL, the maximum output power of the DE- and PSO-based PVARs under the observed patterns (P_{\max}) are compared with the output power of the reference pattern ($P_{\max_{ref}}$), as stated in Equation (7)

$$\%PL = \frac{P_{\max} - P_{\max_{ref}}}{P_{\max_{ref}}} \times 100\% \quad (7)$$

The fitness of the algorithms is analyzed, and the result is shown in the next section. Each generation produced a selected PVAR with its corresponding output power, and the maximum output power is assumed to have been achieved when a solution converges. The best algorithm should converge faster with high accuracy and maximum power.

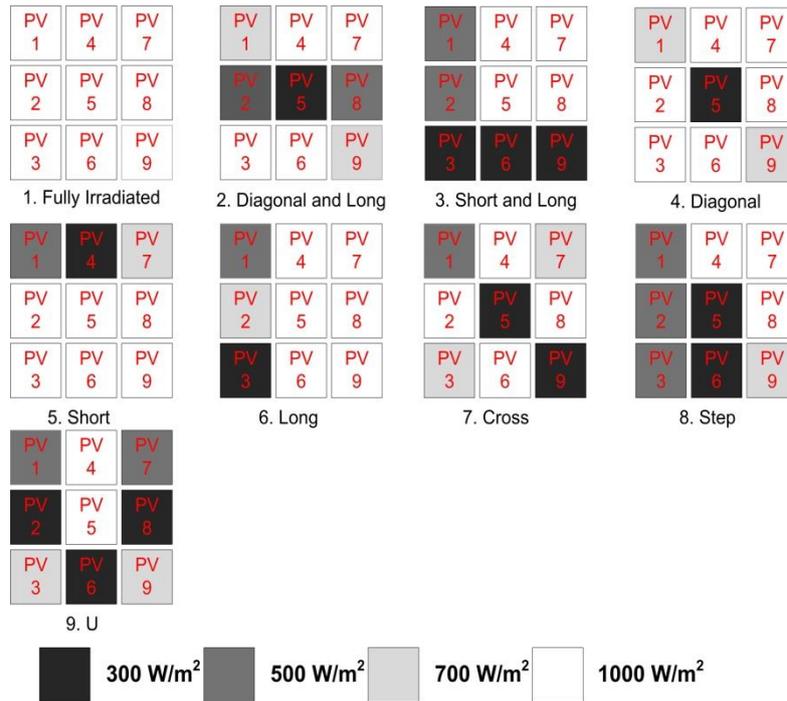


Figure 7. Shading patterns

6. RESULTS AND DISCUSSION

The performance of the proposed DE-based PVAR is observed from the result of the analyses. After 25 generations of DE and PSO algorithms are completed, the $P-V$ characteristics of both algorithms are compared to analyze the power loss, as illustrated in Figure 8. The %PL of the DE-based PVAR on the diagonal and long, short, long, cross, step, and U patterns are lower than that of the PSO-based PVAR. The remaining patterns show that the %PL for both algorithms is similar. To summarize, DE-based PVAR is the ideal technique to yield energy from the PV array because it produces the highest P_{max} and has low power losses under most PS patterns.

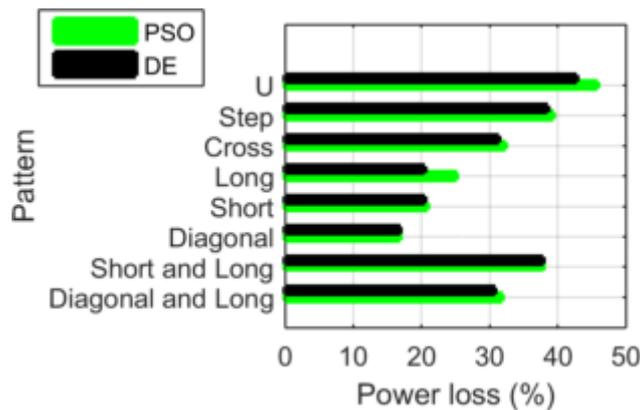


Figure 8. Power loss percentages

Table 1 shows that the fastest maximum output power achieved by DE-based PVAR is at Generation = 7 during the short pattern. However, PSO converges faster at Generation=1 under the step pattern. For all patterns, PSO converges to the maximum output power earlier than DE. However, its solution is not optimal because the output power is not at maximum. Thus, DE has better accuracy and optimum output power. PSO converges faster but lacks accuracy and has a tendency to be trapped at local peaks. Therefore, DE is considered the most efficient algorithm to be used as an optimizer for PVAR, given that the

primary objective of this work is to extract the optimal output power from the PV array during PS occurrences.

Table 1. Number Of Generations To Achieve Steady State

Pattern	Number of generations to achieve steady state	Number of generations to achieve steady state
	for DE	for PSO
Diagonal and Long	18	4
Short and Long	23	3
Diagonal	19	3
Short	7	4
Long	11	7
Cross	20	3
Step	12	1
U	13	6

Figure 9 shows the representation of PVAR after the DE algorithm performed the optimization operation. As stated in the previous section, the physical positions of the PV modules remain unchanged. Otherwise, the electrical connections of the PV modules are changed between the rows in the PVAR to extract the optimal output power. The results from the reconfiguration also proved that the irradiance equilibrium technique, as mentioned in the literature, is impractical. The technique should have more options for PVAR to optimize the reconfiguration and find the best configuration. Lastly, DE-based PVAR is simple, accurate, practical, and consistent in extracting solar energy under PSC.

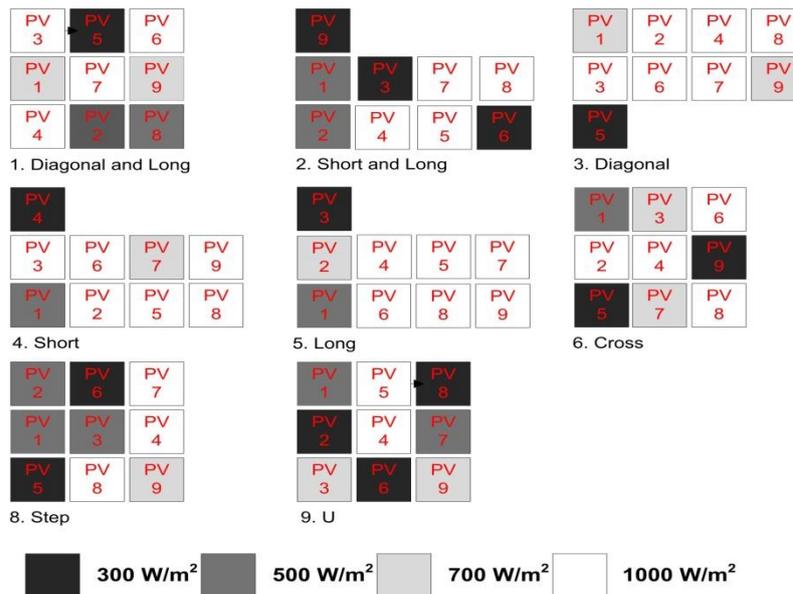


Figure 9. Representation of PVAR after DE optimization operation

7. CONCLUSION

The objective of this work to yield maximum energy from a partially shaded PV array has been achieved successfully. DE-based PVAR performs well, as proven by various PS patterns. DE-based PVAR extracted more power than PSO-based PVAR and static configurations. In addition, DE produced low power losses, thereby helping to maintain the payback period for PV investors. DE-based PVAR is simple and easy to implement in practice. The PVAR circuit is connected to the *I-V* tracer to record the data. Furthermore, the experiment can be conducted under a real irradiance value and PSC. Moreover, DE-based PVAR increases awareness of the use of green energy. This study is expected to encourage more investors to show interest in the PV industry.

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