Comparative Study of Population-Based Algorithms for Solar PV Array Reconfiguration System for Partial Shading Conditions

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2022 22nd National Power Systems Conference (NPSC) | 978-1-6654-6202-0/22/$31.00 ©2022 IEEE | DOI: 10.1109/NPSC57038.2022.10069258

***Abstract*—Photovoltaics are one of the widely used renewables and play an indispensable role in meeting the increased energy demand in recent times. Partial shading condition occurs due to non-uniform irradiance across the PV panels which greatly reduces the efficiency and output of the PV plants. Several techniques were developed as a tool to reduce the vulnerability of partial shading in literature out of which PV array reconfiguration system is found to be a competent technique for obtaining the maximum power in such conditions. The dynamic reconfiguration of PV system is accomplished by redistributing the modules based on their shading levels. Therefore, this paper compares different algorithms based on population such as Differential Evolution (DE), Rao's optimization, Particle Swarm Optimization (PSO), Reptile Search Algorithm (RSA) and Manta Ray Foraging Optimization (MRFO) aiming to provide the optimum pattern for PV reconfiguration to produce maximum power output under varied conditions of partially shaded PV array. The presented work considers PV array in total-cross-tied (TCT) configuration and the results are compared considering the metrics like maximum power output obtained and fill factor.**

I. Introduction

Among the various available renewable energy sources, photovoltaics have become the most dominant and sustainable due to their abundance, high reliability and non-detrimental nature. An important phenomenon which causes substantial curtailment of photovoltaic output is partial shading condition (PSC). PSC refers to availability of non-uniform irradiation across the PV panels that occurs because of tree shadows & buildings, bird droppings, dust particles, passing clouds, defects during manufacturing process and non-uniform ageing. During PSC, the shaded modules in a photovoltaic string receive reduced amount of irradiation and hence generate less current. This acts as a load, draining power from the healthy modules creating a temperature rise leading to hot-spots. Several methodologies have indeed been documented in recent times to get over the impact of partial shading. Usage of bypass diodes across the PV modules to render alternate route for current to avoid power losses taking place in shaded modules is a common solution. It increases the power output but however introduces multiple peaks in the voltage-power characteristics. Different MPPT algorithms were developed to track the global peak of P-V curve efficiently whose practical implementation involves a high number of converters for the power plants of large rating, resulting in increased cost.

Reconfiguration of PV system is lately introduced to be a powerful and efficacious strategy to diminish the influence of shading. This refers to the rearrangement of photovoltaic modules by altering the positions or electrical connections between them as per their illumination for uniform shade dispersion. The basic inter-connection schemes mentioned in the literature include series, parallel, series-parallel, total cross-tied, honey comb and bridge link. Amongst them, the TCT scheme has been examined and proven to be more efficient in the aspects of fill factor and output power. As per the literature, reconfiguration methodologies can be classified into two parts namely static and dynamic reconfiguration of PV array. The physical relocation approach without altering the electrical connection is categorized as a static reconfiguration. The prominent approaches in this class include the Su Do Ku reconfiguration, Zig-zag Technique, Competence Square, Futoshiki Puzzle, Magic Square, Skyscraper Technique etc. In dynamic reconfiguration, the shade distribution is acquired by dynamically modifying the PV module's electrical interconnections without changing the physical arrangement by using switches, sensors, and control algorithms. These techniques include Electrical Array Reconfiguration (EAR), Irradiance Equalization (IE), Adaptive Array Reconfiguration (AAR) and using Artificial Intelligence (AI).

In this piece of work, a comprehensive comparison of Differential Evolution (DE), Reptile Search Algorithm (RSA), Rao's optimization, Particle Swarm Optimization (PSO) and Manta Ray Foraging Optimization (MRFO) techniques is carried out for dynamic PV reconfiguration. The performance is assessed using a weighted objective function for a 9x9 PV array with varied shading patterns for providing the optimal

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reconfigured structure.

II. System model

A. Photovoltaic Cell

A PV system's most basic component is the photovoltaic cell which converts the incident light energy in to electrical energy. There are various mathematical models proposed in the literature to represent a solar cell among which single-diode model is commonly preferred considering its effectiveness and ease of design. A PV cell's electrical circuit consists of current source which is ideally linked across the anti-parallel diode. The model can be developed more accurately including the practical considerations by adding parallel leakage resistance R_{sh} and series contact resistance R_s. By applying KCL, the current of a pv cell can be estimated as:

$$I_{pv} = I_{ph} - I_d - I_{sh} \tag{1}$$

I_{ph} is light generated current, I_{sh} is current passing through resistor connected in shunt and I_d represents current through diode in anti-parallel.

$$I_d = I_o\left(exp\left(\frac{V_d}{aV_t} - 1\right)\right)$$

$$I_{sh} = \frac{V + IR_s}{Rsh}$$

in which I_o is the diode saturation current with *a* being the diode's ideality factor and the thermal voltage V_t. V_t is given as ($N_s kT/q$) in which N_s represents the number of series cells, k denotes the Boltzmann constant which is equal to $1.3805 \times 10^{-23} J/K$, q is the electron charge with a value of $1.6 \times 10^{-19} C$ and T refers to PV cell's temperature in Kelvin. The current developed from a PV source as a function of temperature and solar irradiance is

$$I_{ph} = \frac{G}{Go}[I_{sc} + k_i(T - T_o)]$$

where I_{sc} refers to the current at short-circuit given at standard test conditions which are G_o=1000W/m^2 and T_o=25^{o}C. k_i is the current coefficient factor and G, T being the actual irradiation and temperature values respectively.

B. TCT Connection of PV Array

Among various PV array topologies presented in the literature, TCT configuration is observed to be the widely utilized one due to its advantages over other topologies in mitigating the partial shading phenomenon and enhancing the output. This scheme can be formed by connecting cross ties in such a way that the modules of a single row are linked in parallel, while the modules of a column are joined in series. The total row currents and the array voltage for a 9×9 connected TCT array can be calculated as

$$I_{R_i} = \sum_{j=1}^{9}\left(\frac{G_{ij}}{G_o} I_{m_{ij}}\right) \tag{2}$$

$$V_{array} = \sum_{i=1}^{9} V_{m_i} \tag{3}$$

I_{R_i} is the current generated at row i and V_{array} is the complete voltage existing at the array terminals. $I_{m_{ij}}$ and V_{m_i} are the module current and voltage at row i respectively.

III. Population-based algorithms for PV array reconfiguration

A. Differential Evolution

1) Initialization: Initial population is generated randomly in the required interval of the variable which is given as

$$x(i) = x_L + rand \cdot (x_H - x_L) \tag{4}$$

where *x(i)* denotes the ith population member. x_H, x_L being the upper and lower bounds respectively of the variable *x*, *rand* is a randomly selected number in interval [0,1].

2) Mutation: A donor vector is generated in the mutation process by summing up the scaled difference of first two vectors to the third one.

$$D_{i,g+1} = x_{r_1,g} + F_m \cdot [x_{r_2,g} - x_{r_3,g}] \tag{5}$$

in which *g* indicates the present generation and *g+1* indicates the upcoming generation. $x_{r_1,g}$, $x_{r_2,g}$, $x_{r_3,g}$ are randomly chosen vectors for a considered parameter vector $x_{i,g}$ and F_m is the mutation factor whose value is generally taken between 0 & 1.

3) Crossover: This incorporates the better solutions from previous generation to present generation extending the diversity of individuals by creating a trail vector according to cross-over probability C_p.

$$T_{i,g+1} = \begin{cases} D_{i,g+1}, & rand \le C_p \\ x_{i,g}, & otherwise \end{cases} \tag{6}$$

rand is a randomly chosen number in [0,1].

4) Evaluation and Selection: This operator selects the offspring of the succeeding generations by comparing the fitness values of target vector and trail vector.

$$x_{i,g+1} = \begin{cases} T_{i,g+1}, & if\ f(T_{i,g+1}) > f(x_{i,g}) \\ x_{i,g}, & otherwise \end{cases} \tag{7}$$

where *f* is the fitness function whose evaluation is described in the later sections. The best individual in the population is interpreted as

$$x_{b,g+1} = argmax\{f(x_{i,g+1})\} \tag{8}$$

where $x_{b,g+1}$ represents the best solution of the population.
All the above operators are executed until the termination criteria is reached and the finest solution attained so far is approximated to be the optimal desired solution.

B. Particle Swarm Optimization

PSO is a prominent population-based technique used for solving stochastic non-linear optimization problems which is grounded on the study of swarms such as bird flocking and fish schooling. It initiates out with a swarm of particles (or solutions) in which the position and velocity of every particle is modified in the available search space through a number of generations. The velocity update equation of classical PSO is given as follows

$$V_{i,It+1} = w \cdot V_{i,It} + c_1 r_1 (P_{best} - x_{i,It}) + c_2 r_2 (G_{best} - x_{i,It}) \tag{9}$$

where *It* stands for the iteration number and *i* corresponds to the optimization vector with r_1,r_2 being randomly selected numbers in [0,1]. *V*, *x* indicates the velocity and position of the particles where as P_{best}, G_{best} indicates the local and global best positions respectively. c_1, c_2 are called cognitive and social learning factors respectively which tackle the exploration and exploitation phases. *w* is the inertia factor that reflects the memory behaviour of particle. The position of the particles in the swarm is updated using

$$x_{i,It+1} = x_{i,It} + V_{i,It+1} \tag{10}$$

To update the velocity of the particle, a constriction factor χ is inserted for improving the ability of algorithm to converge at best optimal solution effectively.

$$V_{i,It+1} = \chi\{w \cdot V_{i,It} + c_1 r_1 (P_{best} - x_{i,It}) + c_2 r_2 (G_{best} - x_{i,It})\} \tag{11}$$

The values of c_1, c_2 are fixed to 2.05. Inertia factor is taken as unity and constriction factor χ is taken to be 0.729.

C. Rao Optimization Algorithm

Rao algorithm is a self adaptive population based optimization technique that is simple and effective for solving real world optimization problems. This is a metaphor-less technique and optimizes by delving in to the search space on the basis of interaction of a population member with best, worst and randomly selected solutions. A random function is used to interconnect all of them in such a manner that optimal solution is obtained. The governing equation is

$$Z_{i_{n+1}} = Z_{i_n} + rand_1(Z_{g_n} - |Z_{l_n}|) + rand_2(Z_{i_n} - Z_{j_n}) \tag{12}$$

where $Z_{i_{n+1}}$ refers to the solution of i^{th} member at iteration n+1. Z_{i_n} and Z_{j_n} are the solutions of the randomly selected i^{th} and j^{th} members at n_{th} iteration respectively. Z_{l_n}, Z_{g_n} are the worst, best arrived solutions at n_{th} iteration respectively and rand1, rand2 being random values in interval [0,1].

D. Reptile Search Algorithm

Reptile Search Algorithm is a meta-heuristic optimizing approach which is population-based and inspired by social behaviour of crocodiles. The basic RSA is described in two stages:

1) Exploration: The exploratory stage of RSA is explained by the encircling behaviour of crocodiles performing a global search through extensive and wide research. High walk and belly walk are the two crocodile movements observed in this stage while encircling the prey.

$$z_{(i,j)}(t+1) = \begin{cases} B_j(t) - \eta_{(i,j)}(t) \times \beta - R_{(i,j)}(t) \times rand, & t \leq T/4 \\ B_j(t) \times z_{(r_1,j)} \times ES(t) \times rand, & t \leq 2T/4 \ \& \ t > T/4 \end{cases} \tag{13}$$

where *T* denotes the count of maximum iterations and *t* denotes the current iteration. $B_j(t)$ is the obtained best solution so far for j^{th} position and $\eta_{(1,j)}$, $R_{(i,j)}$ are the hunting operator and reduce function respectively for j^{th} position in i^{th} solution. *rand* is a randomly taken number in interval (0,1), β being a sensitive parameter controls exploration accuracy whose value is fixed to 0.1. r_1, r_2 are the random numbers between [1,N] in which N denotes the total number of solutions. $x_{(r_1,j)}$ indicates a randomly chosen position and evolutionary sense *ES(t)* refers to the probability ratio with the values randomly decreasing between 2 and -2.

$$\eta_{(i,j)} = B_j(t) \times P_{(i,j)}$$

$$R_{(i,j)}(t) = \frac{B_j(t) \times z_{(r_2,j)}}{B_j(t) + \epsilon}$$

$$ES(t) = 2 \times r_3 \times \left(1 - \frac{1}{T}\right)$$

in which $P_{(i,j)}$ indicates percentage variation between j^{th} location of best result and current solution and r_3 indicates a randomly selected integer in the range -1 and 1.

$$P_{(i,j)} = \alpha + \frac{z_{(i,j)} - M(z_i)}{B_j(t) \times (UB_j - LB_j) + \epsilon}$$

where *M(z_i)* denotes the average positions of i^{th} solution with *UB*, *LB* being the upper and lower bounds respectively. α is the sensitive parameter whose value is taken as 0.1.

$$M_{z_i} = \frac{1}{N} \sum_{j=1}^{n} z_{(i,j)}$$

2) Exploitation: Exploitation stage in RSA is characterized by the hunting behaviour of crocodiles which is carried out in two phases namely hunting co-ordination and cooperation.

$$z_{(i,j)}(t+1) = \begin{cases} B_j(t) \times P_{(i,j)}(t) \times rand, & t \leq \frac{3T}{4} \ \& \ t > \frac{2T}{4} \\ B_j(t) \times -\eta_{(i,j)}(t) \times \epsilon - R_{(i,j)}(t) \times rand, & t \leq T \ \& \ t > \frac{3T}{4} \end{cases} \tag{14}$$

E. Manta Ray Foraging Optimization

MRFO is a swarm intelligence technique which is inspired from the foraging behaviour of aquatic beings called manta rays. They feed on plankton by implementing three effective strategies named as chain, cyclone and somersault foragings.

1) Chain Foraging: In this, manta rays line up from head to tail to create a single solid foraging chain assuming the best solution to be the plankton with higher concentration found so far. The first manta ray moves towards the prey plankton while the remaining manta rays move in the direction of food and as well as the preceding manta ray.

$$z_{i,d}(t+1) = \begin{cases} z_{i,d}(t) + r \cdot (z_{b,d}(t) - z_{i,d}(t)) + \alpha \cdot (z_{b,d}(t) - z_{i,d}(t)), & \text{i=1} \\ z_{i,d}(t) + r \cdot (z_{i-1,d}(t) - z_{i,d}(t)) + \alpha \cdot (z_{b,d}(t) - z_{i,d}(t)), & \text{i=2,...,N} \end{cases} \tag{15}$$

$$\alpha = 2 \times r \times \sqrt{|log(r)|}$$

$z_{i,d}(t)$, $z_{b,d}(t)$ are the i^{th} positions of individual and best solution respectively at the time t in d^{th} dimension. And, r being a randomly chosen vector in [0,1] with the weight coefficient α.

2) Cyclone Foraging: Manta rays execute cyclone foraging technique when a school of plankton are found in the deep waters. A long foraging chain is created while moving towards the food in a helical path in which each individual simultaneously moves in a spiralling motion towards the prey and also following the preceding manta ray.

$$z_{i,d}(t+1) = \begin{cases} z_{b,d}(t) + r \cdot (z_{b,d}(t) - z_{i,d}(t)) + \beta \cdot (z_{b,d}(t) - z_{i,d}(t)), & \text{i=1} \\ z_{b,d}(t) + r \cdot (z_{i-1,d}(t) - z_{i,d}(t)) + \beta \cdot (z_{b,d}(t) - z_{i,d}(t)), & \text{i=2,...,N} \end{cases} \tag{16}$$

in which

$$\beta = 2e^{r_1 \frac{T-t+1}{T}} \sin(2\pi r_1)$$

β is the weight coefficient, r_1 is selected randomly in [0,1] and T represents the total number of iterations.

3) Somersault Foraging: The individuals are updated to adjust around the best position observed so far in this foraging behaviour. Manta rays somersault to and fro around the food viewing it as a pivot point.

$$z_{i,d}(t+1) = z_{i,d}(t) + S(r_2 \times z_{b,d} - r_3 \times z_{i,d}(t)), \text{i=1,...,N} \tag{17}$$

in which S denotes the somersault factor indicating the somersault range of manta rays whose value is taken to be two. r_2 and r_3 are randomly selected in [0,1].

IV. Objective function for PV Reconfiguraion

The basic requirements of any optimization techniques to begin with, is to construe the objective function. To obtain the maximum output for the reconfigured PV system, the fitness function can be formulated to maximize the array power while minimizing the error power.

$$fitness(i) = Array_{power} + \left(\frac{W_e}{P_e}\right) + (P_{array} \times W_{P_{array}}) \tag{18}$$

in which *fitness(i)* denotes the value of fitness of the current population's i^{th} element. $Array_{power}$ is the overall array power, and P_e denotes the error disparity existing between maximum power output acquired by photovoltaic curve and the local values of power for each row. The array output without using bypass diodes is referred to as P_{array}. The terms $W_{p_{array}}$ and W_e are the weighting factors for P_{array} and P_e respectively whose values are set to 10.

$$Array_{power} = \sum_{i=1}^{9}(I_i \times V_i) \tag{19}$$

in which I_i and V_i corresponds to current values and voltage of photovoltaic array for i^{th} row.

$$P_e = \sum_{i=0}^{9} |P_p - (I_i \times V_i)| \tag{20}$$

where P_p is the peak value of output and the product $I_i \times V_i$ refers to the other local values of power in x^{th} row. This aids in achieving a consistent dispersion for the shading levels, leading to one peak in the PV characteristics.

V. Results and Analysis

To review and illustrate the most reliable strategy for PV array reconfiguration technique under PSC, assessment and comparisons were carried out on the considered algorithms (DE, PSO, Rao, RSA and MRFO). The algorithms are implemented for a population size of 50 and 300 iterations. SM55 PV module is considered whose parametric values are: V_{oc}=21.7V, I_{sc}=3.45A, V_{mpp}=17.4V, I_{mpp}=3.15A. Three types of shade patterns were given as input to a PV array of size 9×9 arranged in TCT scheme and compared on the basis of maximum amount of generated power and fill factor. The simulations are conducted on a laptop with MATLAB version of 2018a.

I_{RI}	I(A)	V(V)	P(W)
I_{R7}	$3.6I_M$	$9V_M$	$32.4V_MI_M$
I_{R8}	$3.6I_M$	$9V_M$	$32.4V_MI_M$
I_{R9}	$3.6I_M$	$9V_M$	$32.4V_MI_M$
I_{R1}	$6.6I_M$	$6V_M$	$39.6V_MI_M$
I_{R2}	$6.6I_M$	$6V_M$	$39.6V_MI_M$
I_{R3}	$6.6I_M$	$6V_M$	$39.6V_MI_M$
I_{R4}	$6.6I_M$	$6V_M$	$39.6V_MI_M$
I_{R5}	$6.6I_M$	$6V_M$	$39.6V_MI_M$
I_{R6}	$6.6I_M$	$6V_M$	$39.6V_MI_M$

(A)

I_{RI}	I(A)	V(V)	P(W)
I_{R1}	$5.2I_M$	$9V_M$	$46.8V_MI_M$
I_{R4}	$5.2I_M$	$9V_M$	$46.8V_MI_M$
I_{R8}	$5.3I_M$	$7V_M$	$37.1V_MI_M$
I_{R9}	$5.3I_M$	$7V_M$	$37.1V_MI_M$
I_{R2}	$5.4I_M$	$5V_M$	$27V_MI_M$
I_{R5}	$5.6I_M$	$4V_M$	$22.4V_MI_M$
I_{R6}	$5.9I_M$	$3V_M$	$17.7V_MI_M$
I_{R7}	$6.1I_M$	$2V_M$	$12.2V_MI_M$
I_{R3}	$6.4I_M$	$1V_M$	$6.4V_MI_M$

(B)

I_{RI}	I(A)	V(V)	P(W)
I_{R2}	$5.3I_M$	$9V_M$	$47.7V_MI_M$
I_{R5}	$5.3I_M$	$9V_M$	$47.7V_MI_M$
I_{R7}	$5.4I_M$	$7V_M$	$37.8V_MI_M$
I_{R4}	$5.5I_M$	$6V_M$	$33V_MI_M$
I_{R9}	$5.5I_M$	$6V_M$	$33V_MI_M$
I_{R6}	$5.6I_M$	$4V_M$	$22.4V_MI_M$
I_{R3}	$5.7I_M$	$3V_M$	$17.1V_MI_M$
I_{R1}	$6I_M$	$2V_M$	$12V_MI_M$
I_{R8}	$6.1I_M$	$1V_M$	$6.1V_MI_M$

(C)

I_{RI}	I(A)	V(V)	P(W)
I_{R1}	$5.3I_M$	$9V_M$	$47.7V_MI_M$
I_{R4}	$5.3I_M$	$9V_M$	$47.7V_MI_M$
I_{R7}	$5.3I_M$	$9V_M$	$47.7V_MI_M$
I_{R8}	$5.3I_M$	$9V_M$	$47.7V_MI_M$
I_{R6}	$5.5I_M$	$5V_M$	$27.5V_MI_M$
I_{R2}	$5.7I_M$	$4V_M$	$22.8V_MI_M$
I_{R3}	$5.8I_M$	$3V_M$	$17.4V_MI_M$
I_{R5}	$6I_M$	$2V_M$	$12V_MI_M$
I_{R9}	$6.2I_M$	$1V_M$	$6.2V_MI_M$

(D)

I_{RI}	I(A)	V(V)	P(W)
I_{R1}	$5.4I_M$	$9V_M$	$48.6V_MI_M$
I_{R2}	$5.4I_M$	$9V_M$	$48.6V_MI_M$
I_{R3}	$5.4I_M$	$9V_M$	$48.6V_MI_M$
I_{R7}	$5.4I_M$	$9V_M$	$48.6V_MI_M$
I_{R8}	$5.6I_M$	$5V_M$	$28V_MI_M$
I_{R9}	$5.7I_M$	$4V_M$	$22.8V_MI_M$
I_{R4}	$5.9I_M$	$3V_M$	$17.7V_MI_M$
I_{R6}	$6.2I_M$	$2V_M$	$12.4V_MI_M$
I_{R5}	$6.4I_M$	$1V_M$	$6.4V_MI_M$

(E)

I_{Ri}	I(A)	V(V)	P(W)
I_{R1}	$5.4I_M$	$9V_M$	$48.6V_MI_M$
I_{R2}	$5.4I_M$	$9V_M$	$48.6V_MI_M$
I_{R3}	$5.4I_M$	$9V_M$	$48.6V_MI_M$
I_{R4}	$5.4I_M$	$9V_M$	$48.6V_MI_M$
I_{R7}	$5.4I_M$	$9V_M$	$48.6V_MI_M$
I_{R8}	$5.6I_M$	$4V_M$	$22.4V_MI_M$
I_{R9}	$5.7I_M$	$3V_M$	$17.1V_MI_M$
I_{R5}	$5.9I_M$	$2V_M$	$11.8V_MI_M$
I_{R6}	$6.4I_M$	$1V_M$	$6.4V_MI_M$

(F)

Fig. 1: Analysis of pattern 1: (A)TCT (B)DE (C)Rao (D)RSA (E)PSO (F)MRFO

The computation of row currents for TCT connection as a sample are given as :

The current values are same for row 1 to 6 which can be calculated as given: I_{R_1} to I_{R_6} = (900/1000)*6 I_M + (400/1000)*3 I_M = 6.6 I_M. The current values for remaining

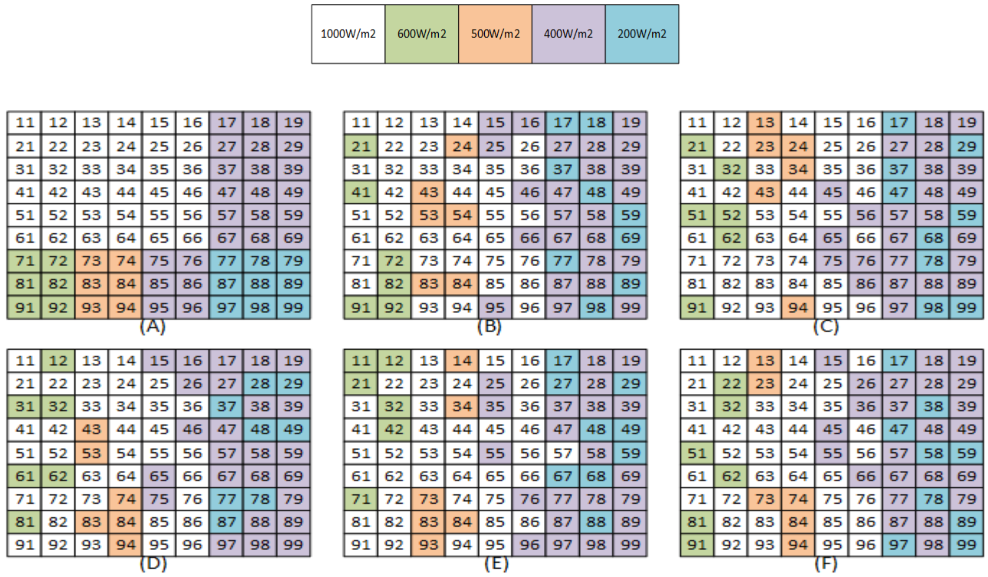

Fig. 2: Pattern 1: (A)TCT (B)DE (C)Rao (D)RSA (E)PSO (F)MRFO

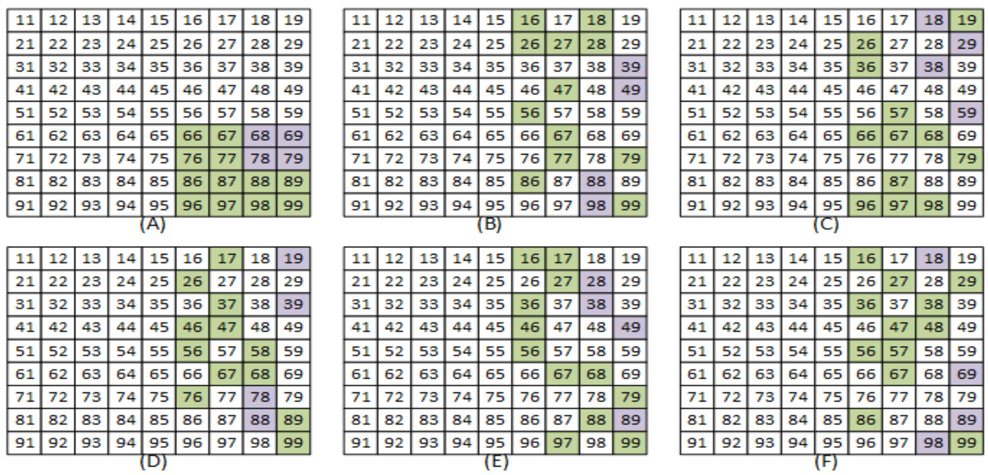

Fig. 3: Pattern 2: (A)TCT (B)DE (C)Rao (D)RSA (E)PSO (F)MRFO

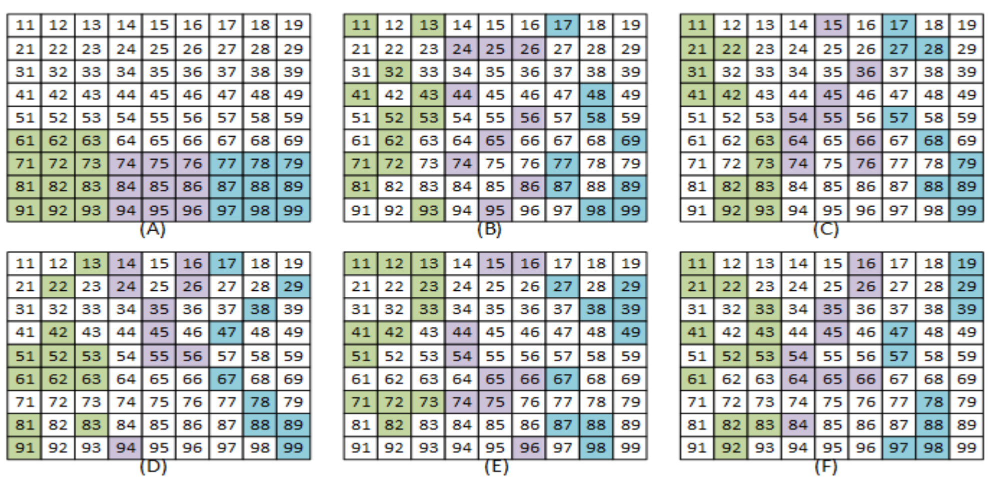

Fig. 4: Pattern 3: (A)TCT (B)DE (C)Rao (D)RSA (E)PSO (F)MRFO

TABLE I: ANALYSIS OF VARIOUS SHADE PATTERNS

(a) PATTERN 1

Method	I(I)	P(W)
TCT	3.6I$_M$	32.4V$_M$I$_M$
DE	5.2I$_M$	46.8V$_M$I$_M$
Rao	5.3I$_M$	47.7V$_M$I$_M$
RSA	5.3I$_M$	47.7V$_M$I$_M$
PSO	5.4I$_M$	48.6V$_M$I$_M$
MRFO	5.4I$_M$	48.6V$_M$I$_M$

(b) PATTERN 2

Method	I(I)	P(W)
TCT	6.5I$_M$	58.5V$_M$I$_M$
DE	7.2I$_M$	64.8V$_M$I$_M$
Rao	7.2I$_M$	64.8V$_M$I$_M$
RSA	7.3I$_M$	65.7V$_M$I$_M$
PSO	7.3I$_M$	65.7V$_M$I$_M$
MRFO	7.3I$_M$	65.7V$_M$I$_M$

(c) PATTERN 3

Method	I(I)	P(W)
TCT	3.6I$_M$	32.4V$_M$I$_M$
DE	5.9I$_M$	53.1V$_M$I$_M$
Rao	6.1I$_M$	54.9V$_M$I$_M$
RSA	6.1I$_M$	54.9V$_M$I$_M$
PSO	6.2I$_M$	55.8V$_M$I$_M$
MRFO	6.3I$_M$	56.7V$_M$I$_M$

three rows are given as I$_{R_7}$ to I$_{R_9}$ = (600/1000)*2 I$_M$ + (500/1000)*2 I$_M$ + (400/1000)*2 I$_M$ + (200/1000)*3 I$_M$ = 3.6 I$_M$. Similarly, the currents of each row for other schemes are also calculated and multiplied with the array voltage to obtain the values of maximum power in terms of I$_M$ and V$_M$. Fig.1 provides a detailed calculation of row currents, array voltages and their respective power values depicting the row current equalisation by each technique for pattern 1. The maximum powers in terms of I$_M$ and V$_M$ obtained by different methods for three shading patterns are summarized in Table I. The efficacy of the above implemented techniques is compared in terms of fill factor whose formula is given as

$$Fill factor(FF) = \frac{(V_{mpp} I_{mpp})_{PSC}}{V_{oc} I_{sc}} \tag{21}$$

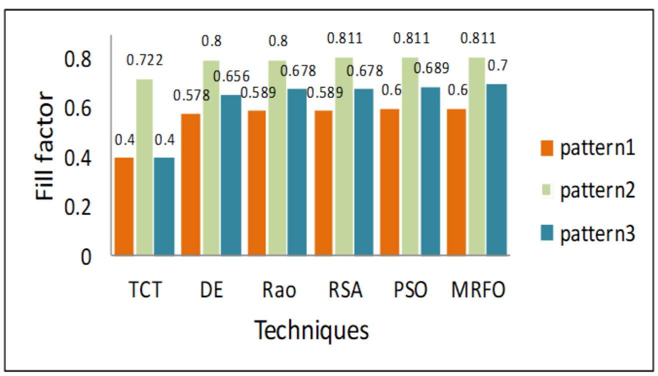

Fig. 5: Fill factor for various shade patterns

Fig. 5 gives the comparative performance of different optimization techniques. It can be observed that MRFO provides the best solution for all patterns whereas DE does not perform at par with other optimization techniques.

VI. Conclusion

In this paper, five optimization techniques, namely DE, PSO, Rao, RSA and MRFO are compared against the basic TCT interconnected arrangement for producing the optimal reconfiguration of a 9×9 photovoltaic array during PSC. It is tested for three different shading patterns and performance metrics such as fill factor and power maximisation are assessed. The analysis suggests that the MRFO technique achieves better performance and good power improvement with reduced losses and higher fill factor in providing the optimal reconfigured structure in the situations where the PV array is exposed to partially shaded conditions.

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