Multi-Objective Grey Wolf Optimizer for Optimal Design of Switching Matrix for Shaded PV array Dynamic Reconfiguration

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ABSTRACT One of the worst negative phenomena faced by photovoltaic (PV) array is the operation under the shadow phenomenon, which significantly affects the generated power. Multiple local maximum power point (MPP) and unique global MPP are generated from the shaded array. Therefore, regular dispersion of the shadow falling on the PV array surface is a vital issue to extract the GMP via reconfiguration of the shaded modules in the array. This article proposes a recent approach based on Multi-objective grey wolf optimizer (MOGWO) to reconfigure the shaded PV array optimally. The main objective of the proposed MOGWO is providing the optimal structure for the switching matrix to minimize the row current difference and maximize the output power. The benefits of the proposed strategy is performing a dynamic reconfiguration process which closes to the reality. The proposed method is validated across 9 × 9 PV array with six shade patterns. MOGWO schemes results are compared with TCT and modified SuDoKu based on several statistical metrics. The comparison reveals the superiority of MOGWO in tackling the multi-peak issue in the P-V characteristics with harvesting the highest power levels.

INDEX TERMS Multi-objective grey wolf optimizer, grey wolf optimizer, total-cross-tied, PV reconfiguration, partial shading.

I. INTRODUCTION Nowadays renewable energy sources (RES) have significantly penetrated in many engineering applications as alternatives to fossil fuel sources as the latter have adverse effects on the environment where they cause global warming. A solar power generation is a form of RESs depending on photovoltaic (PV) modules that converts the sunlight into electricity. The solar power generation system is characterized by less maintenance, zero carbon, and no noise. Despite the importance and benefits of solar energy, it still suffers from some problems like the lack of permanent availability; its characteristic is nonlinear and dependent on the environmental conditions. PV panels are connected in series, parallel, or both to configure array employed in covering a load with immense power. There are various arrangement schemes of PV panels in the array, such as series-parallel (SP), total cross-tied (TCT), Bridge linked TCT (BL-TCT), Honey-comb (HC), Bridge linked Honey-comb (BL-HC) and puzzle pattern. The operation of PV array under shadow conditions has a significant negative impact on the global maximum power (GMP) as it is weakened due to the power loss and hot spots generated on the panels’ surfaces. To avoid this negative phenomenon, a maximum power point tracker based on artificial neural network (ANN) [1] and ANN with an augmented state feedback precise linearization (AFL) controller for the DC/DC converter in [2] have been proposed to extract the GMP and to adaptive act with the fast and sudden changes in the irradiance levels. Moreover, the distributed MPPT techniques have been addressed in [3], multilevel inverter MPPT [4],
and optimization algorithms based DC-DC converter MPPT have been proposed in [5]–[7]. Another alternative solution has been recently proposed for handling the harm impact of the partial shading phenomenon is that rearranging the shaded modules in the array, this process is defined as a reconfiguration of the PV array.

The main target of the PV array reconfiguration process is to minimize the power loss and enhance the GMP. Many researchers presented different topologies of the shaded PV array either via static or dynamic reconfiguration process, some of the reported works are discussed as follows: Horoufi-ny et al. [8] presented a PV reconfiguration process using Sudoku puzzle pattern to minimize the shading effects on the PV array performance. In [9], a strategy based on permanent PV array architecture to rearrange the shaded modules in the array, has been presented. The modules are connected in total cross-tied, TCT, with the odd-even pattern. Sanseverino [10] presented TCT configured PV array with mitigating the effect of mismatch and enhancing the maximum extracted power from the array. Balato et al. [11] performed a reconfiguration process of a series-parallel connected shaded PV array to maximize the output energy and minimize the localized heating produced via bypass diodes and hot spots. The power mismatch loss of shaded PV array has been reduced via constructing different topologies of the array [12]. Akrami and Pourhossein [13] presented a strategy of power comparison to reconfigure the PV array operated under shadow conditions such that maximizing the extracted power. The Marian predator optimization algorithm (MPA) has been implemented to provide the optimal structure for large scale PV array in [14] to tackle the partial shading impact. Yousri et al. [15] proposed modified version of the harris hawk optimizer to reconfigure the shaded PV array to boost the produced power of the system. Fathy [16] presented a methodology based on the grasshopper optimization algorithm, GOA, to reconfigure the shaded PV array, the main target is to enhance the output power. Static and dynamic strategies employed to reconfigure the shaded PV array optimally have been reviewed by Krishna and Moger [17]. The genetic algorithm, GA, has been used for enhancing the output power of the shaded PV array connected in TCT via the reconfiguration process [18]. three different optimizers including the flow regime algorithm (FRA), the social mimic optimization algorithm (SMO), and the Rao optimization algorithm have been proposed in [19] to provide the optimal design for the switching matrix.

Many static approaches used in reconfiguring the shaded PV array to maximize its extracted energy have been reviewed in [20]. Parlak [21] presented a recent approach of configuration scanning algorithm to rearrange the shaded modules in the PV array, such that maximizing the output power. The presented algorithm depends on the short circuit current at a specific portion of the array. In [22], the dominance square method has been employed to obtain puzzle-based reconfiguration of PV array operated under shadow conditions. A column index methodology based on physical relocation of the shaded PV modules incorporated in the array has been presented by Pillai et al. [23] to enhance the output power. The competence square approach has been presented in [24] as a tool to reconfigure the PV modules in TCT connected array to enhance its maximum power. A shade dispersion based on two-phase methodology has been presented to relocate the panels in the array [25]. The minimization of the PV losses due to the shadow effects has been taken in [26] as the target in the rearranging process of the panels. Belhaousas et al. [27] presented three physical configurations of the PV array via maximizing the distances between the neighbor panels such that the adverse effects of shadow are minimized. In [28], the interconnection of panels in TCT connected array has been forecasted to distribute the shading effects normally such that the output power is maximized. Satpathy et al. [29] considered the PV array output power and power loss generated under shadow pattern as the targets employed in the reconfiguration process of the array. In [30], two puzzle architectures based on Ken-Ken and Skyscraper for TCT connected shaded PV array has been presented. Arrow Sudoku puzzle pattern has been used via Tatabhatla et al. [31] to mitigate the mismatch of the row currents of the PV array operated under shadow through the reconfiguration process. Vaidya and Wilson [32] reduced two- dimensional shaded PV array in a one-dimensional string using the time-domain array-reconfiguration approach. Switching control has been used in [33] to perform dynamic reconfiguration of PV array subjected to shadow conditions such that the maximum output power is maximized. An improved Sudoku pattern has been presented to rearrange the shaded PV panels connected in TCT for enhancing the array output power [34], [35]. Standard deviation genetic algorithm, SDGA, has been introduced by Rajan et al. [36], it determined the connection matrix of the PV array configuration to mitigate the shadow effects. Three configurations of the shaded PV array have been investigated in [37]. Pachauri et al. [38] introduced a control scheme-based, Arduino, for rearranging the PV panels in shaded array to enhance the output power. Braun et al. [39] presented an optimized configured shaded PV array to mitigate the mismatch of row currents. A model based on mixed-integer quadratic programming for reconfiguring the PV array has been introduced in [40] to minimize the shadow effects. In [41], [42], a fixed scheme of PV reconfiguration to reduce the shading effects and enhance the array output power, has been presented. Babu et al. [43] introduced particle swarm optimization, PSO, to relocate the PV modules subjected to shadow with improving the output power.

As outlined before, in recent years, the bio-inspired algorithms consort as novel techniques for the PV reconfiguration task. With this inventiveness, the authors in [15], [16], [18], [43] proposed GA, PSO, GOA, and HHO algorithms, respectively. These authors introduced a weighted objective function to achieve the target of maximum power generation. These algorithms confirmed better performance; however, there exist numerous limitations. The obvious limitations are namely i) These algorithms comprise of gigantic
computational steps, ii) They exhibit inconsistent behavior in the system response. iii) They suffered from the slow rate of convergence. iv) The optimal response of the system fully depends on additional tunable parameters. v) In addition, the weight factors used in the objective function of GA [18], PSO [43] and GOA [16] are determined by trial and error method, this requires immense time. Further, the awkward selection of parameter values reflects the failure of the algorithm in achieving the optimal solution. Thereby, the power generated by the system drastically reduces.

To eradicate the issues of existing optimization algorithms, in search of simpler and faster algorithms, research is going on to produce efficient algorithms for the application of solar PV reconfiguration. Therefore, in this article, the multi-objective grey wolf optimizer (MOGWO) is employed for providing the optimal structure for the switching matrix to tackle the issue of adjusting the weights of the objective function to guarantee the reliability and the efficiency of the system. The aim of the proposed approach is minimizing the difference among the maximum and minimum row current levels as a first objective and maximizing the produced power from the regarded array as a second objective. The introduced MOGWO is applied to a series of shade patterns over 9 × 9 PV array. The obtained results by MOGWO are compared with modified SuDuKo and TCT schemes via several statistical measures to appraise the performance of the proposed approach. The results exhibit the superiority of MOGWO in producing the highest power values and smooth PV characteristics.

The remaining parts of the papers are ordered as follows: section II presents the implemented PV equivalent circuit. The TCT scheme explanation is documented in section III. The proposed MOGWO approach with the executed objective functions is clarified in section IV. Section V introduces the results and the analysis for the MOGWO-based reconfiguration system under the studied shade patterns. The statistical metrics are reported in section VI and followed by the conclusion in section VII.

II. PV MODULE MODELING
The efficiency of any PV plant depends on its effective PV modules used in the system. PV module is developed by integrating the number of PV cells. A PV cell is the rudimentary element of PV systems. Due to this, the modeling of PV cells attains the highest priority by researchers. In addition, the non-linear behavior of PV cells modeling becomes a challenging task [44]. By performing numerous experimentation’s authors developed three types of diode models for enhancement of power generation: single-diode (SD) [45], the two-diode (DD) [46], [47], and the three-diode model (TD) [48]. Among these three models, SD is the most widely used one due to its numerous features [49], [50]. In this article, the authors considered the single diode model for the implementation of PV array due to its simplicity in design, involves fewer parameters, and also the most widely used model in real-time applications. The SD has five parameters namely \( I_{pv}, I_0, R_s, a \) and \( R_p \). With a combination of all these parameters, the electrical model of SD is fabricated. The representation of SD is delineated in Fig. 1. The \( I - V \) characteristics of SD is given by the Eq. 1 [6].

\[
I = I_{pv} - I_0 \left( \exp \left( \frac{q(V + R_s I)}{aK} \right) - 1 \right) - \frac{(V + R_s I)}{R_p} \tag{1}
\]

where, \( I_{pv} \) and \( V \) refers the measured I-V data that is obtained from PV cell, \( I \) is the total current generated by PV, \( q \) is charge of electron \( (1.602 \times 10^{-19} \text{C}) \), \( I_0 \) is the diode leakage current, Boltzmann constant \( k \) \( (1.3806503 \times 10^{-23} \text{J/K}) \), \( T \) is temperature in Kelvin. \( a \) ideality factor, \( R_s, R_p \) are series and shunt resistances.

III. TCT-CONNECTED PV ARRAY
TCT is the one type of PV connection, which is most extensively used to accomplish the rated amount of power. By executing the numerous analysis of various types of connection systems, TCT is recommended as an admirable connection scheme for solar PV plants. The TCT connection scheme is confined by interfacing cross-ties over each row of a series-parallel connection. In this article, the authors contemplated a 9 × 9 TCT PV array to certify the proposed MOGWO technique. The TCT scheme is delineated in Fig. 2. This TCT-connected scheme comprises of 9 rows and 9 columns. Each PV module is indicated by \( x, y \), where \( x \) and \( y \) indicate rows and columns, respectively.

The total current and voltage of a TCT connected PV array can be calculated as given in Eq. 2 and Eq. 3, respectively.

\[
I_{out} = \sum_{y=1}^{9} I_{xy}, \quad x = 1, 2, \ldots, 8, 9 \tag{2}
\]

\[
V_{array} = \sum_{x=1}^{9} V_{mx} \tag{3}
\]

where \( I_{out} \) is the PV array total current produced, \( V_{array} \) is the total voltage that appears across terminals of the PV array, and \( V_{mx} \) is the PV module voltage at row \( x \).

To accomplish the most extreme power from the considered PV array, the occurrence shadow ought to scatter...
The prey. The mathematical formulation of the three steps can be modeled as follow; 

- **Attacking prey**: The final stage of the prey survival as the wolves attacking and successfully catching it. This process is satisfied through shrinking the values of the vector $E$.

GWO algorithm was implemented for solving single-objective optimization problems. Whereas for optimizing the multi-objective tasks, Mirjalili et al. [51] proposed another version for GWO called multi-objective grey wolf optimizer (MOGWO) that inherits the primary mechanism of GWO. MOGWO, however, concerns the problems where the optimal resolutions are taken in the presence of trade-offs among two or more contradictory objectives.

### IV. MULTI OBJECTIVE GREY WOLF OPTIMIZER (MOGWO)

GWO is one of the attractive algorithms for the researches due to its simplicity and its adaptive tuning. Mirjalili et al. [51] inspired the main idea of the GWO from the hunting hierarchy of grey wolves pack in natural. The wolves in the pack are classed as alpha ($\alpha$), beta ($\beta$), and delta ($\delta$), then finally omega ($\omega$) ones. The first three classes are responsible for the hunting process by following certain strategies that can be summarized as tracking, encircling, hunting, and attacking the prey. The mathematical formulation of the three steps can be modeled as follow;

- **Tracking the prey**: As a first step, the wolves diverge randomly to search for their prays; this can be modeled mathematically based on the following equation:

\[
\vec{D} = |\vec{B} \cdot U_{\text{rand}}(J) - \vec{U}(J)|
\]

\[
\vec{U}(J + 1) = U_{\text{rand}}(J) - \vec{E} \cdot \vec{D},
\]

where $j$ adopts for the current iteration, $E$ and $B$ are coefficient vectors, the symbol of $||$ illustrates the absolute value, $\vec{r}_1$, $\vec{r}_2$ are random vectors in [0 1], and $a$ is a linearly decreasing function from 2 to 0 across the iteration numbers. The $U_{\text{rand}}$ is a random location vector and $\vec{U}$ is the current location vector of the grey wolves.

- **Encircling prey**: By detecting the location of the prey by the alpha, beta and delta wolves, the rest of the wolves follow this location based on the mentioned equations below;

\[
\vec{D} = |\vec{B} \cdot U_{\text{p}}(J) - \vec{U}(J)|
\]

\[
\vec{U}(J + 1) = U_{\text{p}}(J) - \vec{E} \cdot \vec{D},
\]

where $U_{\text{p}}$ is the location vector of the prey.

- **Hunting prey**: In this stage, the wolves have a certain knowledge about the prey location and the other wolves followed toward it to hunt. This behavior can be formulated mathematically by the following equations;

\[
\vec{D}_\alpha = |\vec{B}_1 \cdot U_{\text{p}} - \vec{U}|; \quad \vec{D}_\beta = |\vec{B}_2 \cdot U_{\text{p}} - \vec{U}|;
\]

\[
\vec{D}_\delta = |\vec{B}_3 \cdot U_{\text{p}} - \vec{U}|
\]

\[
\vec{U} = \vec{U}_1 + \vec{E}_{\delta} \cdot \vec{D}_\delta
\]

\[
\vec{U}(J + 1) = \frac{\vec{U}_1 + \vec{U}_2 + \vec{U}_3}{3},
\]

where $\vec{B}_1$, $\vec{B}_2$, and $\vec{B}_3$ are random vectors in [0 1], and $a$ is a linearly decreasing function from 2 to 0 across the iteration numbers. The $U_{\text{rand}}$ is a random location vector and $\vec{U}$ is the current location vector of the grey wolves.

- **Attacking prey**: The final stage of the prey survival as the wolves attacking and successfully catching it. This process is satisfied through shrinking the values of the vector $E$.

GWO algorithm was implemented for solving single-objective optimization problems. Whereas for optimizing the multi-objective tasks, Mirjalili et al. [51] proposed another version for GWO called multi-objective grey wolf optimizer (MOGWO) that inherits the primary mechanism of GWO. MOGWO, however, concerns the problems where the optimal resolutions are taken in the presence of trade-offs among two or more contradictory objectives.
Min(Obj$_2$) = $|I_{max} - I_{min}|$, \hspace{1cm} (7b)

where $I_x$ and $V_x$ are the current and voltage of the PV array for the $x^{th}$ row, respectively. The symbol $I$ is rows current vector, $I_{max}$ and $I_{min}$ are the maximum and minimum values of the current in the vector $I$.

The goal of implementing the MOGWO is identifying the optimal structure for the switching matrix that satisfies the trade-off between the aforementioned objective functions. The first objective function targeted to maximize the generated power; however, the second one formed to guarantee the uniform distribution for the shade on the surface of the considered array. For the Multi-objective optimization algorithms, the best non-dominated solutions obtained so far are stored in an archive. Several methods can handle the selection of the best solution. In this work, the designer can decide the considered array, and the incident irradiance levels are varied from 1000 W/m$^2$ to 100 W/m$^2$. MOGWO based reconfiguration is compared with TCT and modified SuDoKu [35] arrangements to demonstrate the superiority of the proposed approach in producing the highest power value with a regular dispersion for the shade over the array surface. Several statistical metrics are implemented for the comparison stage; namely, i) Mismatch power loss ii) Fill factor iii) Percentage of power loss iv) Percentage of power enrichment. The analysis is performed on a laptop with specifications of 4 GB RAM, Core i7, 2.5 GHz of speed processor, and version of MATLAB 2018.

### A. SHADING PATTERN 1 (CASE 1)

In this case, the underside of the right corner of a $4 \times 4$ array is shaded with 600 W/m$^2$ and 400 W/m$^2$, while the remaining modules in the PV array received full irradiation i.e., 1000 W/m$^2$ as given in Fig. 3(a). For the considered TCT scheme, the obtained dispersed shade patterns using Modified SuDoKu and the proposed MOGWO are shown in Fig. 3(b) and Fig. 3(c) respectively. To find the global maximum power, it is obligatory to calculate the currents produced by each row of the TCT scheme, modified SuDoKu, and MOGWO.

From Fig. 3(a), it can be observed that, the PV modules in row 1 to row 5 receive equal amount of irradiations i.e., 1000 W/m$^2$. Thereby the current generated by these 5 rows will be equal. The row currents can be theoretically calculated as follows.

$$I_{RW1 to RW5} = A_{11}I_{11} + A_{12}I_{12} + A_{13}I_{13} + \cdots = -A_{19}I_{19}.$$ \hspace{1cm} (8)

where $A_{11} = G_{11} = 1$, $G_{11}$ and $I_{11}$ are the irradiation received and current generated by PV module 11 respectively. $G_0$ is the standard irradiation i.e., 1000 W/m$^2$. Current generated by each module at full irradiation condition can be assigned as $I_M$. Therefore, the current for the row 1 to row 5 can be given as in Eq. 9

$$I_{RW1 to RW5} = 9 \left( \frac{1000}{1000} \right) I_M = 9I_M.$$ \hspace{1cm} (9)

Similarly, the currents for the remaining rows can be calculated as follows:

- Row currents for $6^{th}$ and $7^{th}$ rows can be given as follows:
  $$I_{RW6} = I_{RW7} = 5 \left( \frac{1000}{1000} \right) I_M + 2 \left( \frac{600}{1000} \right) I_M + 2 \left( \frac{400}{1000} \right) I_M = 7I_M.$$

- Row currents for $8^{th}$ and $9^{th}$ rows can be given as follows:
  $$I_{RW8} = I_{RW9} = 5 \left( \frac{1000}{1000} \right) I_M + 4 \left( \frac{600}{1000} \right) I_M = 7.4I_M.$$
By following the same procedures, the dispersed shade pattern of the proposed MOGWO scheme as in Fig. 3(c), can be given as follows:

- The row current for 1st and 9th rows can be calculated as:
  \[ I_{RW1} = I_{RW9} = 8 \left( \frac{1000}{1000} \right) I_M + 1 \left( \frac{600}{1000} \right) I_M = 8.6I_M. \]

- The row current for 2nd and 4th rows can be calculated as:
  \[ I_{RW2} = I_{RW4} = 7 \left( \frac{1000}{1000} \right) I_M + 2 \left( \frac{600}{1000} \right) I_M = 8.2I_M. \]

- The rows, 3, 6, 7, and 8 follows similar shade pattern, therefore, the current generated by these rows are the same and its currents can be calculated as:
  \[ I_{RW3} = I_{RW6} = I_{RW7} = I_{RW8} = 7 \left( \frac{1000}{1000} \right) I_M + 1 \left( \frac{600}{1000} \right) I_M + 1 \left( \frac{400}{1000} \right) I_M = 8I_M. \]

- The row current for the 5th row can be calculated as:
  \[ I_{RW5} = 7 \left( \frac{1000}{1000} \right) I_M + 2 \left( \frac{600}{1000} \right) I_M = 8.2I_M. \]

After performing the current calculations, the obtained voltage and amount of power tracked via TCT, Modified SuDoKu and the proposed MOGWO for the case 1 are tabulated in Table 1.

From Table 1, it is realized that the proposed MOGWO generates the most enhanced power of 72 \( V_M I_M \) (\( V_M \) is the maximum voltage generated by the PV module) when contrasted with the TCT and Modified SuDoKu. In addition, in the case of proposed MOGWO, there exist only three different powers, whereas Modified SuDoKu attains 9 different values of powers. This indicates the presence of multiple peaks in the P-V curve. When there exist multiples in the P-V curves, obviously, it generates less amount of power. The power generated by Modified SuDoKu is 68.4 \( V_M I_M \), which is a little better than TCT, but it produces more multiple peaks than TCT connected system. To observe the multiple peaks and power, see in Fig. 4. From the data interpreted in Fig. 4, it can be noticed that the proposed MOGWO extracted 13209 W from the reconfigured PV array, whereas the modified SuDoKu and TCT produce 12982 W, and 12074 W respectively. From the obtained curves, it is evident that the proposed MOGWO generate 9.4 % higher power than TCT connected configuration and its voltage close to the PV array nominal operating voltage.

**B. SHADING PATTERN 2 (CASE 2)**

In Case 2, the bottom left corner of 4 x 4 PV modules are shaded with 4 different levels of irradiations such as...
TABLE 1. Analysis of TCT, Modified SuDoKu and MOGWO schemes of case 1.

| TCT arrangement | Modified SuDoKu arrangement [35] | MOGWO arrangement |
|------------------|----------------------------------|-------------------|
| $I_{RW1}$ | $I(A)$ | $V(V)$ | $P(W)$ | $I_{RW1}$ | $I(A)$ | $V(V)$ | $P(W)$ | $I_{RW1}$ | $I(A)$ | $V(V)$ | $P(W)$ |
| $I_{RW7}$ | $7I_M$ | $9V_M$ | $63V_MI_M$ | $I_{RW2}$ | $7.6I_M$ | $9V_M$ | $68.4V_MI_M$ |
| $I_{RW6}$ | $7.4I_M$ | $7V_M$ | $51.8V_MI_M$ | $I_{RW8}$ | $8I_M$ | $8V_M$ | $64V_MI_M$ |
| $I_{RW5}$ | $9I_M$ | $5V_M$ | $45V_MI_M$ | $I_{RW9}$ | $8.2I_M$ | $6V_M$ | $49.2V_MI_M$ | $I_{RW7}$ | $8.2I_M$ | $5V_M$ | $41V_MI_M$ |
| $I_{RW4}$ | $8I_M$ | $8V_M$ | $64V_MI_M$ | $I_{RW9}$ | $8.6I_M$ | $2V_M$ | $17.2V_MI_M$ | $I_{RW9}$ | $8.6I_M$ | $2V_M$ | $17.2V_MI_M$ |

where $I_{RWi}$ is the $i^{th}$ row current.

![1000 W/m², 700 W/m², 400 W/m², 300 W/m²](image)

FIGURE 5. Short wide shadow pattern, (a) TCT scheme, (b) Modified SuDoKu method (c) and MOGWO for case 2.

1000 W/m², 700 W/m², 400 W/m² and 300 W/m². This can be seen from Fig. 5(a). Its obtained reconfigured shade patterns via modified SuDoKu and the proposed MOGWO are presented in Fig. 5(b) and Fig. 5(c) respectively.

By calculating the currents generated from each row of the considered three methods, the voltage and power generated are tabulated in Table 2. From the analysis presented in Table 2, one can detect that the proposed MOGWO method generates a high amount of power $69.3 \ V_MI_M$ compared to TCT and Modified SuDoKu methods. Moreover, it produces less number of power variations, which enhances the power generation. The P-V curves for the case 2 of TCT and dispersed shade patterns are plotted in Fig. 6. From the characteristics, the GMPP obtained via the proposed MOGWO, Modified SuDoKu, and TCT are found to be 12861 W, 12627 W, 11152 W respectively. The GMPP values simulated via MATLAB environment has gauged the proposed MOGWO to achieve immense power. In flow, the modified SuDoKu occupies the 2$^{nd}$ position with generated power of 12627 W. Critical observation made from P-V curves is that the shade dispersed using MOGWO-based arrangement tackles the multi-peaks hence achieved a unique peak. At the more significantly, the obtained GMPP is almost equal to the nominal operating voltage. From the TCT characteristics, it can be observed that change in irradiation levels causes bypassing.
C. SHADING PATTERN 3 (CASE 3)

In case 3, the top right corner of the PV array is shaded, and the considered irradiation profile for this case study is 600 W/m², 400 W/m², and 200 W/m², see in Fig. 7(a). Further, its reconfigured shade pattern using Modified SuDoKu and MOGWO are given in Fig. 5(b) and 5(c) respectively. Based on the dispersion of shade, the calculated voltage, current, and power values are conferred in Table. 3. The proposed MOGWO is able to extract power $68.4\ V_M I_M$, which is much higher than the other two arrangements. The P-V curves that resemble the pattern of case 3 are shown in Fig. 8. The power produced by TCT, Modified SuDoKu, and MOGWO after successful reconfiguration are 10762 W, 12077 W, and 12613 W, respectively. From the P-V curves, it can be noticed that the MOGWO attains a single peak and achieves 17.19 % higher power than TCT connected system.

D. SHADING PATTERN 4 (CASE 4)

In this case, five variant irradiations were considered to showcase the effectiveness of the proposed technique. In Case 4, left top corner of the $4 \times 4$ PV array is subjected to shading
with irradiation levels of 500 \( \text{W/m}^2 \), 300 \( \text{W/m}^2 \), 200 \( \text{W/m}^2 \) and 100 \( \text{W/m}^2 \) and other modules receives full irradiation of 1000 \( \text{W/m}^2 \), can noticed from the Fig. 9(a). The dispersed shade patterns of both modified SuDoKu and the proposed MOGWO are given in Fig. 9(b) and Fig. 9(c) respectively. Similar to the previous cases, to prove the superiority of power generation, the theoretically calculated current, voltage, and power values are tabulated in Table 4. Based on the interpreted in Table 4, the proposed MOGWO generates 66.6 \( V_M I_M \), whereas Modified SuDoKu and TCT extract 59.4 \( V_M I_M \) and 54.6 \( V_M I_M \) respectively. Which very less than the proposed method. The Simulated P-V curves for this case are presented in 10. From the plotted curves, it is noteworthy to highlight that the reconfigured MOGWO technique has manifested its maximum power even at a short wide shadow pattern. In this case, proposed MOGWO produces 12332 W power, which is 18 % and 9 % higher than TCT and Modified SuDoKu, respectively.

**E. SHADING PATTERN 5 (CASE 5)**

In case 5, middle portion of the array faced to shade with 4 type shade levels such as 600 \( \text{W/m}^2 \), 400 \( \text{W/m}^2 \), 300 \( \text{W/m}^2 \) and 400 \( \text{W/m}^2 \). The remaining modules in the PV array exposed to full irradiation of 1000 \( \text{W/m}^2 \). The arrangement of this shade pattern with TCT connected scheme is shown in Fig. 11(a). After performing the reconfiguration process via

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**TABLE 3.** Analysis of TCT, Modified SuDoKu and MOGWO schemes of case 3.

| TCT arrangement | Modified SuDoKu arrangement [35] | MOGWO arrangement |
|-----------------|----------------------------------|-------------------|
| \( I_{RW1} \) | \( I(A) \) | \( V(Y) \) | \( P(W) \) | \( I_{RW1} \) | \( I(A) \) | \( V(Y) \) | \( P(W) \) | \( I_{RW1} \) | \( I(A) \) | \( V(Y) \) | \( P(W) \) |
| \( 6.2 I_M \) | \( 9 V_M \) | \( 56.8 V_M I_M \) | \( 6.8 I_M \) | \( 9 V_M \) | \( 61.2 V_M I_M \) | \( 7.8 I_M \) | \( 9 V_M \) | \( 68.4 V_M I_M \) | \( 7.8 I_M \) | \( 7 V_M \) | \( 54.6 V_M I_M \) | \( 8.2 I_M \) | \( 2 V_M \) | \( 16.4 V_M I_M \) |
| \( 6.1 I_M \) | \( 7 V_M \) | \( 46.2 V_M I_M \) | \( 7.7 I_M \) | \( 5 V_M \) | \( 38.5 V_M I_M \) | \( 8 I_M \) | \( 4 V_M \) | \( 32 V_M I_M \) | \( 8 I_M \) | \( 3 V_M \) | \( 24 V_M I_M \) | \( 8.1 I_M \) | \( 3 V_M \) | \( 23.4 V_M I_M \) |
| \( 9 I_M \) | \( 5 V_M \) | \( 45 V_M I_M \) | \( 8.1 I_M \) | \( 3 V_M \) | \( 24.3 V_M I_M \) | \( 8.1 I_M \) | \( 1 V_M \) | \( 8.6 V_M I_M \) | \( 8.2 I_M \) | \( 2 V_M \) | \( 16.4 V_M I_M \) |

where \( I_{RWi} \) is the \( i^{th} \) row current.
D. Yousri et al.: Multi-Objective Grey Wolf Optimizer for Optimal Design of Switching Matrix

Table 4. Analysis of TCT, Modified SuDoKu and MOGWO schemes of case 4.

| TCT arrangement | Modified SuDoKu arrangement [35] | MOGWO arrangement |
|-----------------|---------------------------------|-------------------|
| $I_{RW_1}$ $I_{A1}$ | $V_{(V)}$ $P(W)$ | $I_{RW_1}$ $I_{A1}$ | $V_{(V)}$ $P(W)$ | $I_{RW_1}$ $I_{A1}$ | $V_{(V)}$ $P(W)$ |
| $I_{RW_4}$ 61W | $9V_M$ | 54V$V_M$ | $I_{RW_1}$ 6.61W | $9V_M$ | 59.4V$V_M$ | $I_{RW_1}$ 7.4W | $9V_M$ | 66.6V$V_M$ |
| $I_{RW_3}$ 61W | $9V_M$ | 54V$V_M$ | $I_{RW_1}$ 7.4W | $8V_M$ | 59.2V$V_M$ | $I_{RW_1}$ 7.5W | $7V_M$ | 52.5V$V_M$ |
| $I_{RW_9}$ 91W | $5V_M$ | 45V$V_M$ | $I_{RW_1}$ 7.71W | $6V_M$ | 46.2V$V_M$ | $I_{RW_1}$ 7.71W | $6V_M$ | 46.2V$V_M$ |
| $I_{RW_4}$ 91W | $5V_M$ | 45V$V_M$ | $I_{RW_1}$ 8.1W | $3V_M$ | 24.3V$V_M$ | $I_{RW_1}$ 8.1W | $3V_M$ | 24.3V$V_M$ |
| $I_{RW_6}$ 62W | $4V_M$ | 34V$V_M$ | $I_{RW_1}$ 8.2W | $2V_M$ | 16.4V$V_M$ | $I_{RW_1}$ 8.3W | $1V_M$ | 8.3V$V_M$ |

where $I_{RW_1}$ is the $i^{th}$ row current.

![Figure 11](image1.png)

**FIGURE 11.** Short wide shadow pattern, (a) TCT scheme, (b) Modified SuDoKu method (c) and MOGWO for case 5.

modified SuDoKu and the proposed MOGWO methods, the dispersed shade patterns are given in Fig. 11(b) and Fig. 11(c) respectively. The respective current, voltage, and powers are theoretically calculated and presented in Table 5. Further, the simulated P-V curves for this case are shown in Fig. 12. In this case, one noticed that due to the high and wide shade condition, there exist huge peaks in the P-V curves of the TCT connected system, and the system bypasses the shaded PV modules. Thereby, it generates the current difference, which reflects on multiple peaks. Whereas, the proposed MOGWO eradicates the bypassing of PV modules and achieves unique with the global power of 12661 W, which much higher than TCT and modified SuDoKu.

**F. SHADING PATTERN 6 (CASE 6)**

To test system performance in a different condition, in a case 6, a wide scope of shade events having two irradiation levels are taken into consideration. The two irradiation levels are 600 W/m$^2$, 200 W/m$^2$, and its representation with TCT connected system can observe in Fig. 13(a). Since the different shade type is applied in this case, a shrewd reconfiguration technique that contribute high shade dispersion process need to be appropriately recognized. To estimate the performance of the system, the current, voltage, and power has been estimated similar to earlier cases and presented in Table. 6. In this case, the proposed MOGWO technique generates a

![Figure 12](image2.png)

**FIGURE 12.** P-V Characteristics for case 5.
high amount of power $66.6V_{IM}$ than the other two techniques. The same has been evaluated using the simulation and obtained P-V curves are presented in Fig. 14. In this case, the proposed MOGWO technique generated power 9% and 3% higher than TCT and modified SuDoku.

### VI. PERFORMANCE MEASURES

To assess the excellency of the proposed technique, a critical analysis is made by considering various performance parameters such as mismatch power loss, fill factor, percentage of power loss, and percentage of power enhancement between each technique. As per the formula given by authors in [24], the mentioned analysis has been carried out. After a successful analysis, a synoptic overview is presented to understand the effect of reconfiguration during shade conditions. The review is computed among the proposed MOGWO, TCT, and Modified SuDoku (that appeared as SDU in the figures).

- **Mismatch loss**: Generally, these losses occur when the PV modules failed to function at its maximum power capability. Thereby, it confirms that losses in mismatch power reflect a huge reduction in the output power.

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**FIGURE 13.** Short wide shadow pattern, (a) TCT scheme, (b) Modified SuDoku method (c) and MOGWO for case 6.

**TABLE 5.** Analysis of TCT, Modified SuDoku and MOGWO schemes of case 5.

| TCT arrangement | Modified SuDoku arrangement [35] | MOGWO arrangement |
|-----------------|----------------------------------|-------------------|
| $I_{R4}$ $I_{R6}$ $I_{R8}$ $I_{R10}$ $V_{M}$ $P_{M}$ | $I_{R4}$ $I_{R6}$ $I_{R8}$ $I_{R10}$ $V_{M}$ $P_{M}$ | $I_{R4}$ $I_{R6}$ $I_{R8}$ $I_{R10}$ $V_{M}$ $P_{M}$ |
| $I_{R2}$ $I_{R4}$ $I_{R6}$ $I_{R8}$ $I_{R10}$ $V_{M}$ | $I_{R2}$ $I_{R4}$ $I_{R6}$ $I_{R8}$ $I_{R10}$ $V_{M}$ | $I_{R2}$ $I_{R4}$ $I_{R6}$ $I_{R8}$ $I_{R10}$ $V_{M}$ |
| $I_{R2}$ $I_{R4}$ $I_{R6}$ $I_{R8}$ $I_{R10}$ $V_{M}$ | $I_{R2}$ $I_{R4}$ $I_{R6}$ $I_{R8}$ $I_{R10}$ $V_{M}$ | $I_{R2}$ $I_{R4}$ $I_{R6}$ $I_{R8}$ $I_{R10}$ $V_{M}$ |
| $I_{R2}$ $I_{R4}$ $I_{R6}$ $I_{R8}$ $I_{R10}$ $V_{M}$ | $I_{R2}$ $I_{R4}$ $I_{R6}$ $I_{R8}$ $I_{R10}$ $V_{M}$ | $I_{R2}$ $I_{R4}$ $I_{R6}$ $I_{R8}$ $I_{R10}$ $V_{M}$ |

where $I_{Ri}$ is the $i^{th}$ row current.

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**FIGURE 14.** P-V Characteristics for case 6.

By considering it as an important factor in PV performance, the mismatch losses for the considered the three methods for 6 shade cases are presented in Fig. 15. From the presented bar plots in Fig. 15, it is noteworthy to
mention that TCT and Modified SuDoKu (SDU) attain a high amount of losses, and it occupies high positions in bar plots. Whereas, the proposed MOGWO attains the lowest position in the bar plot, which confirms that, proposed MOGWO betas its performance compared to other techniques. To notice the clear difference in mismatch power loss, the real global power (Real GP) and obtained global powers (Obtained GP) are also plotted in the same in Fig. 15.

- **Fill Factor:** It is the other important parameter for PV plant performance evaluation. The calculated fill factors for the three considered methods are plotted in Fig. 16. The plotted figures reveal the excellent performance of the proposed MOGWO. In all 6 cases, the proposed MOGWO method attains the highest values compared with the other techniques. Thereby, it indicates the reduction in losses and enhances the generated power.

- **% of Power loss:** Estimating the % of Power loss in each technique plays a crucial role in knowing about exact losses in the system. With this motivation, the % of power loss for each case were computed and presented in Fig. 17. From Fig. 17, it can be perceived that proposed MOGWO techniques produce minimized loss than the other two techniques. In case 4, the TCT and Modified SuDoku (SDU) methods produce 28.993 % and 22.295 %, which is much higher than the proposed MOGWO. In case 2, the % of power losses by the MOGWO-rearrangement is closer to the SDU method. However, the small disparity may lead to a high level of in-case of high rated PV plants.

Based on the carried-out analysis and from the interpreted calculations, the necessity and introducing the MOGWO-reconfiguration approach is also evaluated and
FIGURE 16. Fill factor for the studied shading cases, (a) pattern 1, (b) pattern 2, (c) pattern 3, (d) pattern 4, (e) pattern 5 and (f) pattern 6.

FIGURE 17. Percentage power loss for the studied shading cases, (a) pattern 1, (b) pattern 2, (c) pattern 3, (d) pattern 4, (e) pattern 5 and (f) pattern 6.

presented in Fig. 18. The Fig. 18 shows the % of power enhancement of proposed MOGWO with combination TCT and SDU. From this analysis, it can be understood that the implementation of MOGWO-arrangement gives a high amount of power enhancement in all cases. Due to the limitation of Modified SuDoKu (SDU), the combination
of proposed MOGWO and SDU method gives less power enhancement. Thereby it proves the ability to introduce the MOGWO-reconfiguration approach for providing the best structure for the switching matrix.

VII. CONCLUSION
In this manuscript, the authors introduce a novel approach for providing the optimal structure for the switching matrix to solve the problem of mismatch power loss in the shaded PV system. The multi-objective optimization algorithm is proposed to tackle the drawback of the reported algorithms in the literature. Therefore, the authors introduced the multi-objective grey wolf optimizer for dispersing the shaded modules in the considered PV array to minimize the rows’ current levels and maximize the produced power. The new approach is implemented with Matlab/Simulink to be emulated as a real dynamic system for the switching matrix. The proposed method was tested over six different shade patterns with $9 \times 9$ PV array as well as its results are compared with TCT, and the modified SuDoKu methods based on several aspects such as the produced power values, P-V characteristics, mismatch power loss, Fill factor, percentage of power loss and finally the percentage of power enhancement. The comparisons divulged that the MOGWO-arrangement solves the multi-peak issue in the P-V characteristics of the considered array over all the studied shade cases with percentage power enhancement in a range of 9.4 % to 18.8 % from TCT and 1.4 to 8.6 % in comparison with modified SuDoKu.

REFERENCES
[1] S. Ma, M. Chen, J. Wu, W. Huo, and L. Huang, “Augmented nonlinear controller for maximum power-point tracking with artificial neural network in grid-connected photovoltaic systems,” *Energies*, vol. 9, no. 12, p. 1005, Nov. 2016.
[2] M. Chen, S. Ma, J. Wu, and L. Huang, “Analysis of MPPT failure and development of an augmented nonlinear controller for MPPT of photovoltaic systems under partial shading conditions,” *Appl. Sci.*, vol. 7, no. 1, p. 95, Jan. 2017.
[3] S. R. Pendem, S. Mikkili, and P. K. Bonthagorla, “PV distributed-MPP tracking: Total-cross-tied configuration of string-integrated-converters to extract the maximum power under various PSCs,” *IEEE Syst. J.*, vol. 14, no. 1, pp. 1046–1057, Mar. 2020.
[4] L. Xie, J. Qi, G. Weng, and Y. Zhang, “Multi-level PV inverter with photovoltaic groups independent MPPT control,” in *Proc. 17th Int. Conf. Electr. Mach. Syst. (ICEMS)*, Oct. 2014, pp. 829–834.
[5] A. Fathy, H. Rezk, and D. Yousri, “A robust global MPPT to mitigate partial shading of triple-junction solar cell-based system using manta ray foraging optimization algorithm,” *Sol. Energy*, vol. 207, pp. 305–316, Sep. 2020.
[6] D. Yousri, T. S. Babu, D. Allam, V. K. Ramachandaramurthy, and M. B. Eteiba, “A novel chaotic flower pollination algorithm for global maximum power point tracking for photovoltaic system under partial shading conditions,” *IEEE Access*, vol. 7, pp. 121432–121445, 2019.
[7] K. Kaced, C. Larbes, N. Ramzan, M. Bounabi, and Z. E. Dahmane, “Bat algorithm based maximum power point tracking for photovoltaic system under partial shading conditions,” *Sol. Energy*, vol. 158, pp. 490–503, Dec. 2017.
[8] M. Horoufiany and R. Ghandehari, “Optimization of the Sudoku based reconfiguration technique for PV arrays power enhancement under mutual shading conditions,” *Sol. Energy*, vol. 159, pp. 1037–1046, Jan. 2018.
[9] I. Nasiruddin, S. Khatoon, M. F. Jalil, and R. C. Bansal, “Shade diffusion of partial shaded PV array by using odd-even structure,” *Sol. Energy*, vol. 181, pp. 519–529, Mar. 2019.
[10] R. Sansveretino, T. N. Ngoc, M. Cardinale, V. L. Vigni, D. Musso, P. Romanino, and F. Viola, “Dynamic programming and Munksre algorithm for optimal photovoltaic arrays reconfiguration,” *Sol. Energy*, vol. 122, pp. 347–358, Dec. 2015.
[11] M. Balato, L. Costanzo, and M. Vettigli, “Reconfiguration of PV modules: A tool to get the best compromise between maximization of the extracted power and minimization of localized heating phenomena,” *Sol. Energy*, vol. 138, pp. 105–118, Nov. 2016.
[12] N. Mishra, A. S. Yadav, R. Pachauri, Y. K. Chauhan, and V. K. Yadav, “Performance enhancement of PV system using proposed array topologies under various shadow patterns,” *Sol. Energy*, vol. 157, pp. 641–656, Nov. 2017.
[13] M. Akrami and K. Pourhossein, “A novel reconfiguration procedure to extract maximum power from partially-shaded photovoltaic arrays,” *Sol. Energy*, vol. 173, pp. 110–119, Oct. 2018.
[14] D. Yousri, T. S. Babu, E. Beshr, M. B. Eteiba, and D. Allam, “A robust strategy based on marine predators algorithm for large scale photovoltaic array reconfiguration to mitigate the partial shading effect on the performance of PV system,” *IEEE Access*, vol. 8, pp. 112407–112426, 2020.
[15] D. Yousri, D. Allam, and M. B. Eteiba, “Optimal photovoltaic array reconfiguration for alleviating the partial shading influence based on a modified Harris hare optimizer,” *Energy Convers. Manage.*, vol. 206, Feb. 2020, Art. no. 112470.
[16] A. Fathy, “Recent meta-heuristic grasshopper optimization algorithm for optimal reconfiguration of partially shaded PV array,” *Sol. Energy*, vol. 171, pp. 638–651, Sep. 2018.
[17] G. Sai Krishna and T. Moger, “Reconfiguration strategies for reducing partial shading effects in photovoltaic arrays: State of the art,” *Sol. Energy*, vol. 182, pp. 429–452, Apr. 2019.
[18] S. N. Deshkar, S. B. Dhale, J. S. Mukherjee, T. S. Babu, and N. Rajasekar, “Solar PV array reconfiguration under partial shading conditions for maximum power extraction using genetic algorithm,” *Renew. Sustain. Energy Rev.*, vol. 43, pp. 102–110, Mar. 2015.
[19] T. S. Babu, D. Yousri, and K. Balasubramanian, “Photovoltaic array reconfiguration system for maximizing the harvested power using population-based algorithms,” *IEEE Access*, vol. 8, pp. 109608–109624, 2020.
[20] S. Malathy and R. Ramaprabha, “Reconfiguration strategies to extract maximum power from photovoltaic array under partially shaded conditions,” *Renew. Sustain. Energy Rev.*, vol. 81, pp. 2922–2934, Jan. 2018.
[21] K. Ş. Parlak, “PV array reconfiguration method under partial shading conditions,” *Int. J. Electr. Power Energy Syst.*, vol. 63, pp. 713–721, Dec. 2014.
[22] B. Dhanalakshmi and N. Rajasekar, “Dominance square based array reconfiguration scheme for power loss reduction in solar Photovoltaic (PV) systems,” *Energy Convers. Manage.*, vol. 156, pp. 84–102, Jan. 2018.
[23] D. S. Pillai, J. Prasanth Ram, M. Siva Sai Nihanth, and N. Rajasekar, “A simple, sensorless and fixed reconfiguration scheme for maximum power enhancement in PV systems,” *Energy Convers. Manage.*, vol. 172, pp. 402–417, Sep. 2018.
A. Tabanjat, M. Becherif, and D. Hissel, “Reconfiguration solution for solar PV maximum power extraction,” Energy Convers. Manage., vol. 174, pp. 897–912, Oct. 2018.

D. S. Pillai, N. Rajasekar, J. P. Ram, and V. K. Chimnaiyan, “Design and testing of two phase array reconfiguration procedure for maximizing power in solar PV systems under partial shading conditions (PSC),” Energy Convers. Manage., vol. 178, pp. 92–110, Dec. 2018.

P. R. Satpathy and R. Sharma, “Power and mismatch losses mitigation by a fixed electrical reconfiguration technique for partially shaded photovoltaic arrays,” Energy Convers. Manage., vol. 192, pp. 52–70, Jul. 2019.

N. Belhaouas, M.-S.-A. Cheikh, P. Agathoklis, M.-R. Oularbi, T. S. Babu, J. P. Ram, T. Dragičević, M. Miyatake, F. Blaabjerg, and M. Z. Shams El-Dein, M. Kazerani, and M. M. A. Salama, “Optimal configuration of the maximum power extraction under partial shading conditions,” Energy Convers. Manage., vol. 123, pp. 535–548, Sep. 2016.

D. Yousri, D. Allam, M. B. Eteiba, and P. N. Suganthan, “Static and dynamic photovoltaic models’ parameters identification using chaotic heterogeneous comprehensive learning particle swarm optimizer variants,” Energy Convers. Manage., vol. 182, pp. 546–563, Feb. 2019.

D. Allam, D. A. Yousri, and M. B. Eteiba, “Parameters extraction of the three diode model for the multi-crystalline solar cell/module using moth-flame optimization algorithm,” Energy Convers. Manage., vol. 123, pp. 535–548, Sep. 2016.

T. Sudhakar Babu, N. Rajasekar, and K. Sangeetha, “Modified particle swarm optimization technique based maximum power point tracking for uniform and under partial shading condition,” Appl. Soft Comput., vol. 34, pp. 613–624, Sep. 2015.

D. Yousri, T. S. Babu, D. Allam, V. K. Ramachandaramurthy, E. Beshir, and M. B. Eteiba, “Fractional chaos maps with flower pollination algorithm for partial shading mitigation of photovoltaic systems,” Energies, vol. 12, no. 18, pp. 3548, Sep. 2019.

S. Mirjalili, S. Saremni, S. M. Mirjalili, and L. D. S. Coelho, “Multi-objective grey wolf optimizer: A novel algorithm for multi-criterion optimization,” Expert Syst. Appl., vol. 47, pp. 106–119, Apr. 2016.

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