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Design of a MPPT System Based on Modified Grey Wolf Optimization Algorithm in Photovoltaic System under Partially Shaded Condition

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Abstract

Conventional Maximum Potential Monitoring strategies such as perturbation and observation, incremental conduct and climbing can effectively monitor the maximum power point in uniform shading, whereas failing in a partially shaded condition. Nevertheless, it is difficult to achieve optimal and reliable power by using photovoltaics. So, to solve this issue, this article proposes to monitor the photovoltaic system's global optimum power point for partial shading with a Modified Gray Wolf Optimizer (MGWO) based maximum power point tracking algorithm. Under partial shadows, a mathematical model of the PV system is built with a single diode, EGWO is used to monitor global maximum power points. A photovoltaic system includes deciding which converter is used to increase photovoltaic power generation. The MPPT architecture uses a modified gray wolf optimization algorithm to quickly track the output power and reduce photovoltaic oscillations. The efficiency of the maximum power tracker is better than the GWO algorithm of up to 0,4 s with the modified gray wolf optimization algorithm. Converters are used to resolve the power losses often occurring in PV systems with a soft-buck converter process. The output of the power generator is greater than the soft-switching buck converter. The simulation and experimental results obtained suggest that both the P & O and IPSO MPPTs are superior to the proposed MPPT algorithm, the proposed algorithm increases the traceability efficiency. The suggested algorithm has the fastest follow-up speed since the α value decreases during the iteration exponentially.

Keywords: Grey wolf optimization (GWO); Maximum Power Point Tracking (MPPT); Partial shading conditions (PSCs); Photo-voltaic (PV).

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1. Introduction

In energy electronics systems, renewable energy generation in an infinite number of industrial and social applications has become increasingly relevant. The PV systems have become very popular for electricity supply solutions worldwide from all renewable energy sources due to their suitability. Furthermore, [19] notes that energy harvested by photovoltaic systems is expected to be a great choice for both advanced and developing economies as demand for energy will increase by 30% in 2040. (according to [20,26]). Photovoltaic systems are an alternative to conventional energy production in almost every country in the world such as reduced emissions of Greenhouse gas, inexhaustible solar fuel, green nature and so on. India also targets 100 GW of electricity in large and small solar parks by 2022 to meet increasing energy demand [1,23]. The PV system is equally present in single or two-diiodide models and is worked at a maximum power point (MPP) because of its low efficiency to achieve maximum power output [25]. Varied atmospheric conditions impact PV systems, one of these phenomena is partial shading of PV modules (because of cloud passage, Shadows, bird waste, etc. construction). In PSC, its non-linear properties are subject to multiple maximum performance points due to operation PV systems of the bypass diode across shaded modules [2], so operational at a global MPP is necessary. A great deal can be done to mitigate the PSC effect. This task is to run the PV system on the global MPP on PSCs using MPPT controllers. MPPT controllers, PV array resetting's, Power Converter settings, etc [4,5]. Despite traditional MPP techniques, like Perturb & Observe (P&O), Hill Climbing (HC) and others, MPPs are easily tracked under uniform shadow conditions [18]. In literature, several writers have used intelligence-based techniques, including the ANN method and the Fuzzy system to derive full power from the PSC system [9,10]. Meta-heuristic techniques based on MPPT have recently become common due to their accuracy and dependence on the system [3]. Several authors suggested MPPT algorithms focused on the Specific Swarm Optimization [6,7], Ant Colony optimization [14], Firefly [12], Grey Wolf Optimizer [8], and Whale Optimization Algorithms [11,19]. MOP algorithms were also proposed by some writers. MPPT techniques are usually divided by the MPP monitoring section into direct and indirect control methods. All these algorithms vary greatly in precision, performance, time, and complexity of the tracks [13]. It explains that premature convergence problems and even the complexity of the algorithm have limited the use of the algorithm on real PV systems, which must be modified in PSO-based MPPT. The premature algorithm convergence has also been studied in [17], when results show that the classic PSO-based solution might collapse into a local solution to generate larger oscillations as a consequence of the required re-initialization of the algorithm following irradiation changes. (as validated in [21]). In conventional GWO Algorithms, δ and ω, these wolves are not much contributing to the hunting of the prey, as they are subordinated to α and β [15]. This paper deals with alpha and all wolves as the α and β wolves, where alpha is the cattle's chief and the best option, are eliminated by Enhanced MPPT Gray Wolf Optimizer (MGWO). The proposed MGWO, therefore, contributes to a rapid search method to track global MPPs in less time.

2. Proposed system

2.1. Characteristics of PV system under PSC

2.1.1. Photovoltaic module

A single diode model can be represented in a PV cell. Figure 1 displays the single diode PV circuit equivalent scheme [24].

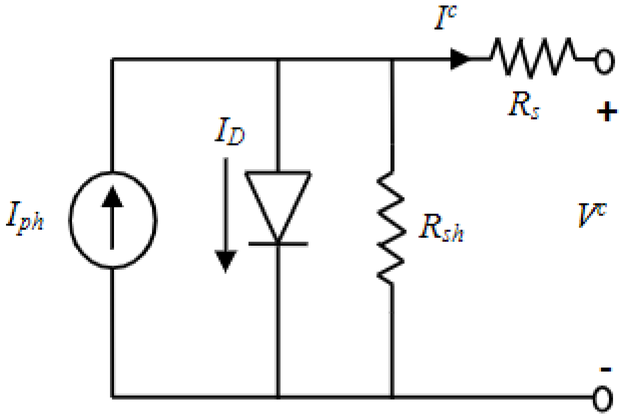


Figure 1: Single diode model PV cell

PV cell model single diode is mostly used in the PV system modeling because its complexities and computer efficiency have been decreased compared with two-diode models as in equation (1) [22,27]:

$$I^c = I_{PV} - I_0 \left[e \left(\frac{q(V^c + I^c R_c)}{KTA} \right) - 1 \right] - \left(\frac{V^c + I^c R_C}{R_{sh}} \right) \tag{1}$$

The PV module output current with Ns of PV cells is defined in (2,3,4,5):

$$I = I_{PV} - I_0 \left[e \left(\frac{q(V^c + IR_c)}{KTA} \right) - 1 \right] - \left(\frac{V^c + IR_C}{R_{sh}} \right) \tag{2}$$

$$I = (I_{PV\_STC} + k_i \Delta T) \frac{G}{G_{STC}} \tag{3}$$

$$I_0 = I_{\circ STC} \left(\frac{T_{STC}}{T} \right)^3 e \left[\frac{qE_g}{AK} \left(\frac{1}{T_{STC}} - \frac{1}{T} \right) \right] \tag{4}$$

$$I_{0\_STC} = \frac{I_{sc\_STC}}{e\left(\frac{qV_{OCSTC}}{N_s A K T_{STC}} \right) - 1} \tag{5}$$

Where V has photovoltage, where Vt is photovoltage, while Vt is photovoltage, where G is photovoltaic voltage (STC). If G = photo course is photovoltaic (STC).

To get the voltage of the module, (2) is modified as in equation (6):

$$V = \frac{N_s K T A}{q} \left[ln \left(\frac{I_{ph} + I_0 - I\left(1 + \frac{R_S}{R_{sh}}\right)}{I_0} \right) \right] - IR_s \tag{6}$$

2.2. Improved GWO and its application in MPPT Design

2.2.1. Overview of Grey Wolf Optimizer

Grey Wolf Optimizer (GWO) is a new meta-heuristic algorithm, which depicts the hierarchy of leadership and caught gray wolves in nature hunting mechanism for non-linear optimism from Swarm Intelligence family and is inspired by gray wolves GWO contains the gray wolves of the Four wolves' types: Beta Alpha Delta and Omega, as shown in figure 2. they are of strict social dominant hierarchy. In GWO, α wolves lead the herd and have an optimization dilemma that is the best solution, β wolves are subordinated to α wolves and assist in the taking of decisions [15].

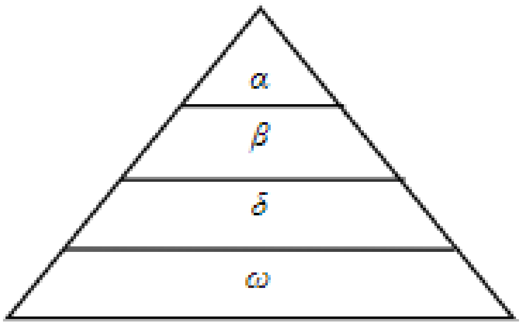


Figure 2: Grey wolves' hierarchy (dominance from top to bottom).

Three main steps are taken to hun. The beta wolf conveys the alpha's messages to other wolves in the group and collects the feedback from the group and conveys the feedback to alpha. The least rated grey wolves are called omega and they are the first ones to attack the prey and eat. If a wolf is not an alpha, beta, or omega then the remaining wolves are called delta and they perform duties like guarding, caretaking of elders, etc [15].

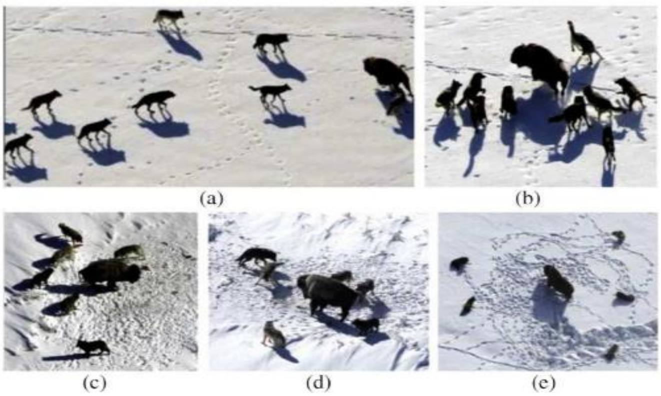


Figure 3: Grey wolf hunting behavior

The leader (α) is known as the best solution for Grey Wolf optimization strategy statistical simulation. The second and third solutions are thus both β and α suit. As mentioned above, the prey is surrounded by wolves during the hunting cycle, so the proposed equations should describe its surroundings (7)-(10).

$$\vec{g} = \left|\vec{e}.\overrightarrow{x_p}(t) - \bar{x}\,(t)\right| \tag{7}$$

$$\vec{x}(t+1) = \overrightarrow{x_p}(t) - \vec{a}.\vec{g} \tag{8}$$

$$\vec{a} = 2\vec{c}.\overrightarrow{r_1} - \vec{c} \tag{9}$$

$$\vec{e} = 2.\overrightarrow{r_2} \tag{10}$$

Where t means the present iteration, $\vec{a}$ and $\vec{e}$ are the vector coefficients, $\vec{x}_p$indicates the prey's location vector and $\vec{x}$ indicates the gray wolf position vector, the random numbers between [0,1] are r1 and r2, the elements of c are reduced linearly from 2 to 0. This method was occasionally undertaken by the hunting of gray wolves, alpha (α) and beta (β), and delta (β). The best and the most vigilant scanners on their prey are the alpha (α), beta (β), and delta (α). The hunting cycle finishes by killing the prey, and the full iteration is completed through the following Equations (11)-(17).

$$\vec{g}_{alpha} = \left|\vec{e}.\vec{x}_{alpha}(t) - \bar{x}\right| \tag{11}$$

$$\vec{g}_{beta} = |\vec{e}.\vec{x}_{beta}(t) - \bar{x}| \tag{12}$$

$$\vec{g}_{delta} = |\vec{e}_2.\vec{x}_{delta} - \bar{x}| \tag{13}$$

$$\vec{x}_1 = \vec{x}_{alpha} - \vec{a}_1\left|\vec{g}_{alpha}\right| \tag{14}$$

$$\vec{x}_2 = \vec{x}_{beta} - \vec{a}_2|\vec{g}_{beta}| \tag{15}$$

$$\vec{x}_3 = \vec{x}_{delta} - \vec{a}_2|\vec{g}_{delta}| \tag{16}$$

$$\vec{x}(t+1) = \vec{x}_1 + \vec{x}_2 + \frac{\vec{x}_3}{3} \tag{17}$$

2.2.2. Modified Grey Wolf Optimization

α and β wolves are submitted to α and β wolves in traditional GWO and are not substantially used for the killing of an ideal solution. This leads to a higher search agent population and time consumption to find the optimum solution. In GWO's proposed β and ω step, the exactness of the optimum solution will be removed completely without compromising. The following are updated steps for evaluating the surrounding and hunting behavior of the proposed MGWO algorithm [15].

- Encircling

Every search officer surrounds the prey during hunting. The conduct is mathematically modeled like in (18-21):

$$\vec{D} = \left|\vec{C}.\overrightarrow{X_p}(t) - \vec{X}_{sg}(t)\right| \tag{18}$$

$$\vec{X}_{sg}(t+1) = \vec{x}_p(t) - \vec{A}.\vec{D} \tag{19}$$

Where t is current iteration and:

$$\vec{A} = 2\vec{a}.\vec{r}_1 - \vec{a} \tag{20}$$

$$\vec{A} = 2.\vec{r}_2 \tag{21}$$

Where A, C are variables that are suitable for balancing the usage by detection, r1, and r2 lead numbers from [0,1] to a linear drop from 2 to 0 has been made.

- Hunting

For each iteration of the following equations, positions of. search agent is modified according to $\vec{X}_a$ and $\vec{X}_\beta$ best search agent positions as in equation (22-24):

$$\vec{D}_a = \left|\vec{C}_1.X_a - \vec{X}_{sg}\right|, \vec{D}_\beta = \left|\vec{C}_2.\vec{X}_\beta - \vec{X}_{sg}\right| \tag{22}$$

$$\vec{X}_1 = \vec{X}_a - \vec{A}_1.(\vec{D}_a), \vec{X}_2 = \vec{X}_\beta - \vec{A}_2.(\vec{D}_\beta) \tag{23}$$

$$\vec{X}_{sg}(t+1) = \frac{\vec{X}_1 + \vec{X}_2}{2} \tag{24}$$

2.3. Application of MGWO for MPPT

For an algorithm, the general approach is to break optimizing into two main issues of the exploration. Exploration encourages unexpected changes which can lead to multiple solutions. The goal of creation is to maintain the consistency of research solutions. In the search area, the algorithm can produce optimal results by testing, while optimization can reduce the range of search results and keep solutions consistent. It is necessary therefore to find optimal results in the right combination of both with demographic algorithms [23]. In GWO, shifting values from a and b are the cause of the transition between discovery and exploitation. In this case, half the discovery is$(|A| \geq 1)$, Yet abuse is the other$(|A| \leq 1)$. In GWO for MPPT, α decreases for any change in equations linearly from 2 to 0, for example, equation (24):

$$a = 2\left(1 - \frac{t}{T}\right) \tag{24}$$

In this case, T indicates the maximum iteration number, α the latest iteration is t. GWO uses an exponential function during the iteration to decrease α for MPPT. The process is called the optimization of the gray wolf (MGWO) as defined in equation (25).

$$a = 2\left(1 - \frac{t^2}{T^2}\right) \tag{25}$$

The main goal is to achieve full P power in the PV array taking into account the decision variable's duty ratio. The target function is therefore established as defined in (26) and (27) [16]:

$$Maximize: P(d) \tag{26}$$

$$Subject: d_{min} \leq d \leq d_{max} \tag{27}$$

where d_{min} and d_{max} are limits of duty ratio.

2.4. Simulation Case Studies

The simulations for 4 PV modules with a serial-parallel configuration under partial shading were performed to validate the proposed MPP. In Figure 4, the machine block diagram is shown. A PV array is included in the block diagram. For the implementation of MPPT, DC-DC interleaved boost converter is used. The MPPT parameter data was used with the voltage and current sensors. MPPT controllers are a load and microcontroller. The following are used for the PV modulization process: Pmax = 100 W, Imp = 5,62 A, Vmp = 17.8 V, Voc = 21,8 V, Isc = 6,05 A: For two series 2 parallels and 4 parallels, the PV modules were related. The components were used for simulation with the DC-DC Interleaved Booster Converter and were picked the experimental system to be L = 244,205 μH, Co = 20,979 μF, and to be 40 kHz. The MGWO flowchart for MPPT is shown in Figure 5.

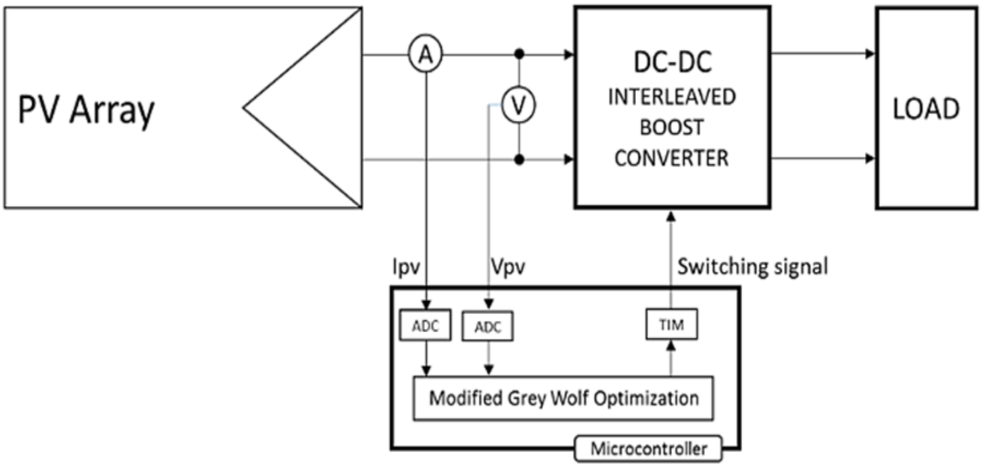


Figure 4: MPPT Process Diagram Proposed

To evaluate the MGWO algorithm performance, the performance of MGWO algorithms was compared to that of GWO (see figures 8 and 9). In partial shading conditions, two methods were applied. The photovoltaic configuration is 4 parallel and 2 parallel series 2. Photovoltain parameters were Pmax for simulation = 100 W, Imp = 5,62 A, Vmp = 17,8 V, Voc = 21,8 V, Isc = 6,05 A. Vin = 17.13 Volt, Vout = 48 V, L = 284.205 μH, C = 20.979 μF, 40 kHz, voltage rib = 1% was chosen for the simulation boost converter configuration.The MATLAB/Simulink configuration is shown in Figure 6 and 7 which represents the whole PV panel. The MATLAB/Simulink configuration is shown in Figure 6 and 7 which represents the whole PV panel.

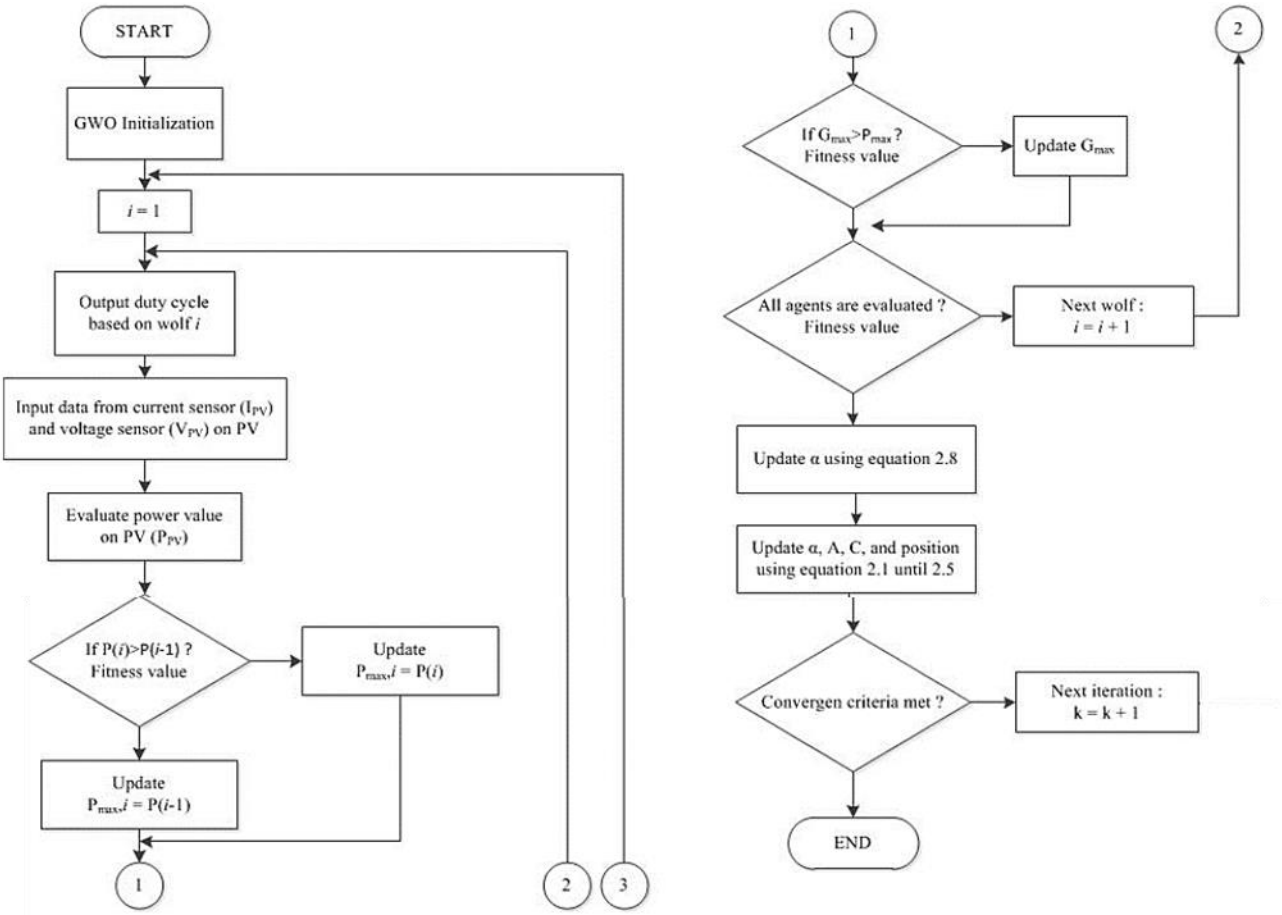
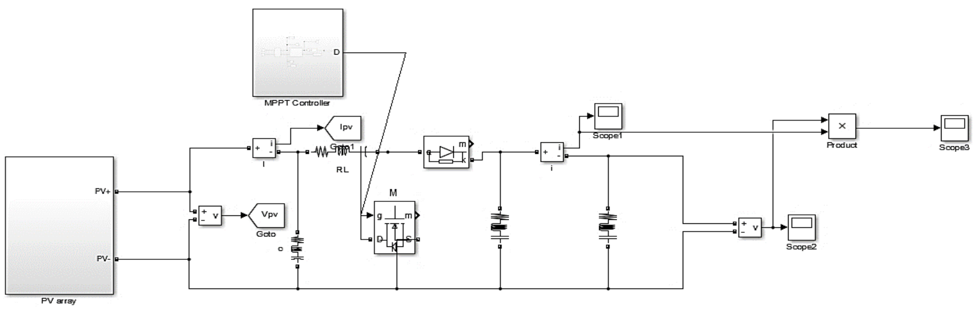


Figure 5: Gray Wolf Optimization Algorithm Improved Flowchart



MPPT design using grey wolf optimization technique for PV system

Figure 6: The proposed model of PV system using Simulink/MATLAB

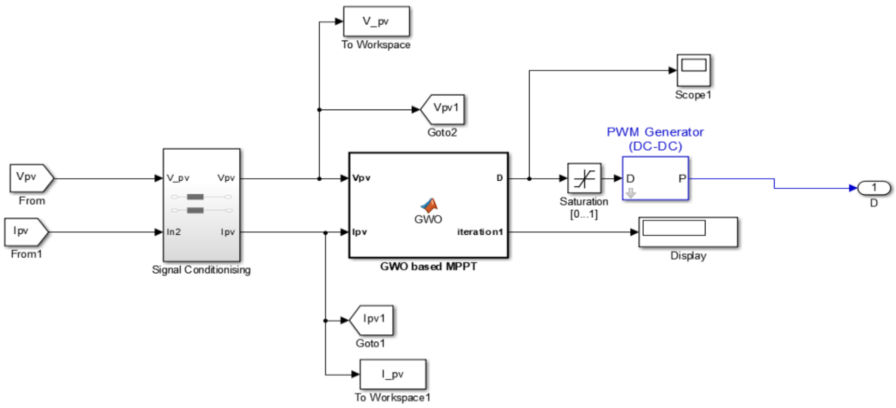


Figure 7: MPPT controller

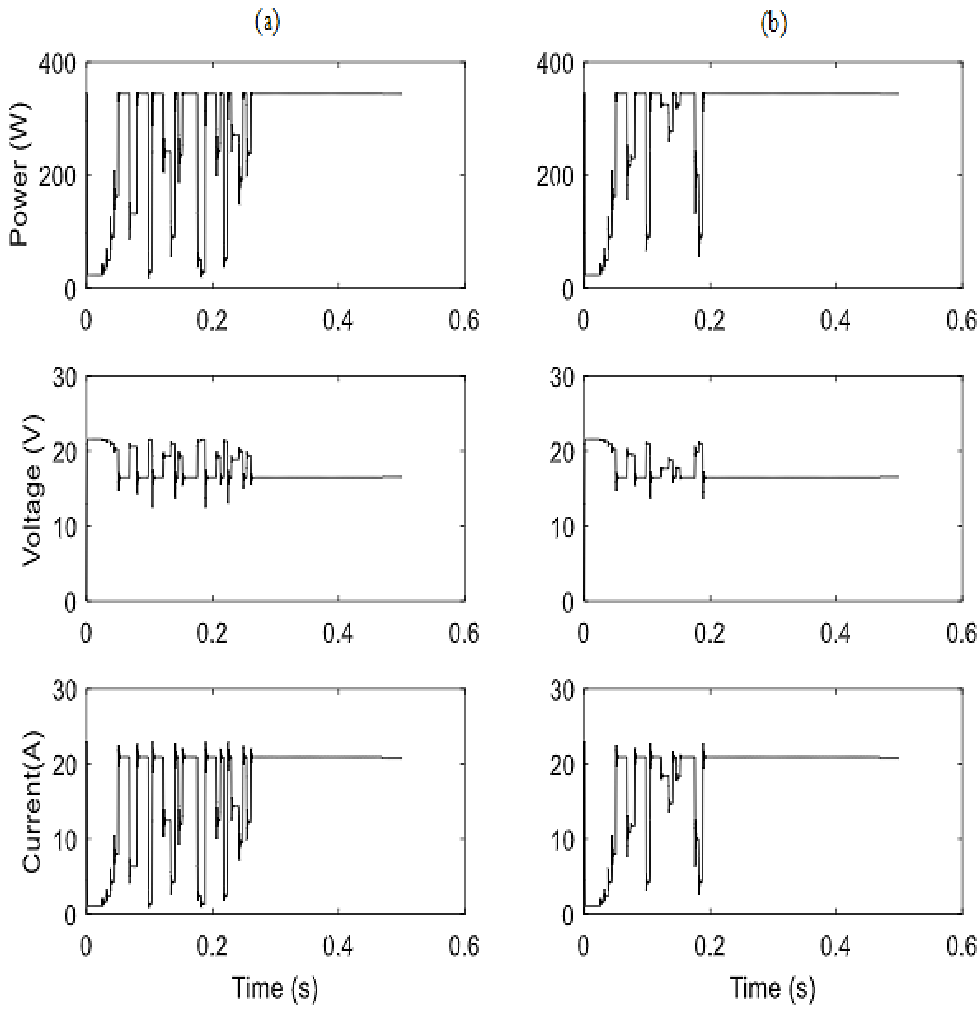


Figure 8: (a) The GWO Simulation Result for MPPT in a photovoltaic combination is 4 parallel. (b) The product of MGWO simulation for photovoltaic combination MPPT is 4.

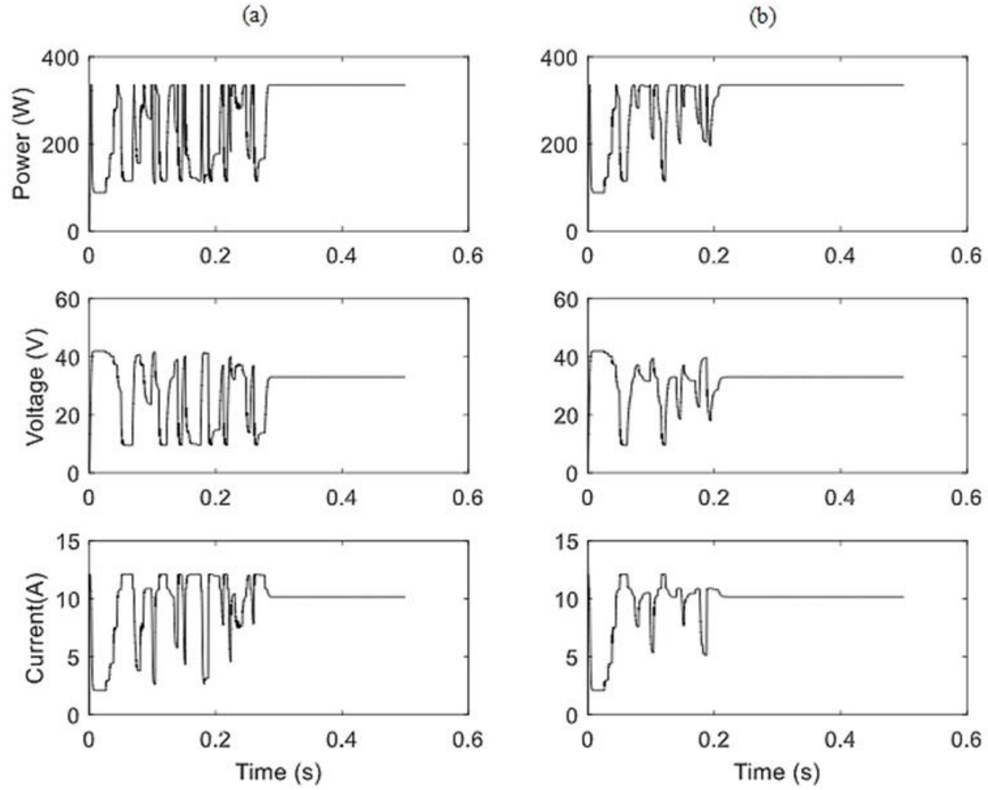


Figure 9: GWO simulation tests for MPPT in photovoltaic combination are 2 parallel series 2 b. MGWO simulation result for MPPT is two series 2 parallel photovoltaics.

Table 1: Non-MPPT and MGWO algorithms in partial shading state Table Contrast

Various Conditions	Tracking Methods	Power (W)	Voltage (V)	Current (A)	Tracking Speed (s)
4 parallel	GWO	443.61	15.873	21.647	0.261
	MGWO	444.65	16.238	21.225	0.189
2 series 2 parallel	GWO	435.56	33.02	10.16	0.284
	MGWO	435.76	32.98	10.18	0.21

In conjunction with P_{pv} in 4 parallels, Figure 8 displays the GWO and MGWO simulation results for MPPT. MPP of 343.61Watts is obtained from the GWO simulation test. In comparison, GWO has a speed of 0.261 s for MPP. The results of the MGWO simulation reach an MPP of 344.65 watts. In addition, GWO has a speed of 0.189 s for MPP. The simulation results for MPPT in combination with PV in 2 Series 2 are shown in Figure 9. MPP of 335,56 watts is obtained from the simulation result of GWO. In comparison, GWO speed is 0.284 s for MPP. MPP is 335,76 Watts for the simulation test of MGWO. In comparison, MGWO has a speed of 0.21 s to achieve MPP. The results of the simulation show that when compared to GWO, the proposed algorithm increases traceability efficiency. The suggested algorithm has the fastest follow-up speed since the α value decreases during the iteration exponentially. The proposed algorithm is perfect for MPP monitoring concerning MPP accuracy. In fact, in contrast with GWO, the algorithm is stronger for the MPP. The proposed MPPT algorithm will lead to the convergence of MPP in Figure 10. In addition, the proposed algorithm will easily achieve MPP. Given the limited oscillations of the proposed MPP algorithm, MGWO performance shows good precision and rapid tracking under partial conditions of shading for MPPT.

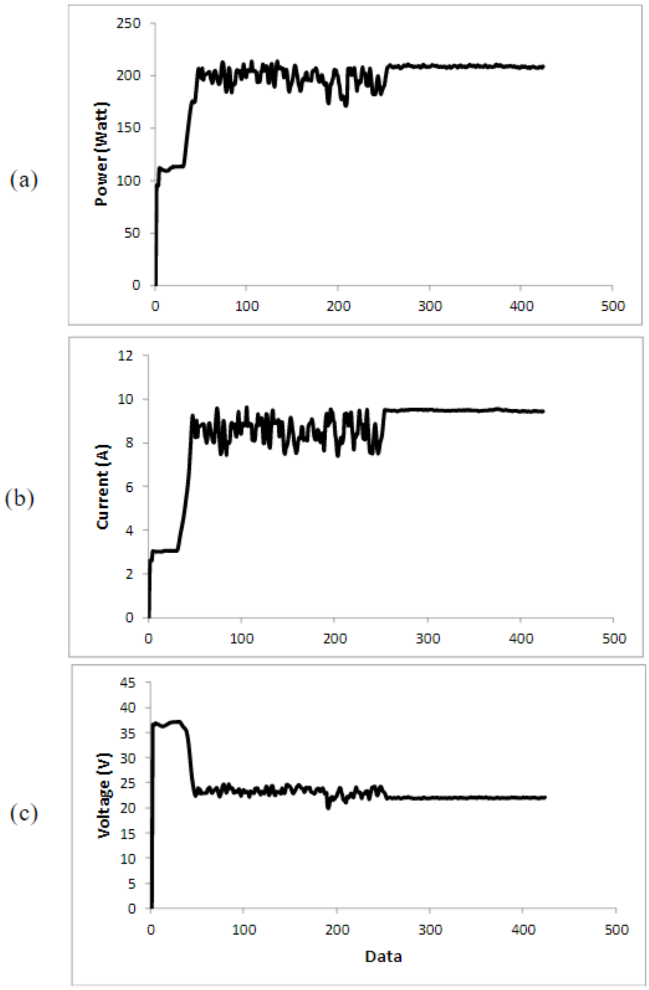


Figure 10: (a) the MGWO partial shading MPPT power trial; (b) the new part-shading MGWO MPPT test; (c) the partial shading voltage trial with MGWO MPPT; (c).

4. Comparison

Table 2: Performance comparison of the proposed MPPT Method For 2s2p Configuration

Shading pattern	Maximum power P-V curve (w)	Tracking technique	Maximum power (w)	Maximum voltage (v)	Maximum current (A)	% Tracking efficiency
1	320	P&O	234	24	9.75	97.78
		IPSO	239.05	25	9.562	99.89
		MGWO	239.01	25.01	9.56	99.91
4	330	P&O	247	23.9	10.3	98.09
		IPSO	251.5	25.64	9.808	99.88
		MGWO	251.6	25.64	9.812	99.92

The findings were contrasted with the P&O and improved PSO (IPSO) algorithm of the MPPT meta-heuristics algorithm proposed by GWO to evaluate the performance. Tables 2 and 3 summarize the simulation findings presented briefly. Table 3 also provides a qualitative contrast between different fast converging MPPT approaches. Tables show that the MPPT dependent on GWO beats the other two MPPT methods.

Table 3: Performance comparison of the proposed MPPT Method For 4s Configuration

Shading pattern	Maximum power from P-V curve (w)	Tracking technique	Maximum power (w)	Maximum voltage (v)	Maximum current (A)	% Tracking efficiency
1	320	P&O	100.2	24.2	1.14	31.30
		IPSO	319.2	110.52	2.888	99.75
		MGWO	319.4	110.55	2.889	99.81
4	330	P&O	180	23.07	7.80	54.54
		IPSO	329.5	112.3	2.934	99.84
		MGWO	329.6	112.3	2.934	99.87

5. Conclusion

This paper provides effective theoretical modeling of a partially shaded PV system. The retrieve of the traditional GWO algorithm is proposed as a stronger GWO MPPT algorithm in order to track the global PV system MPP in a partially-shaded way with more precision and less time to track. The simulation results suggested that in different the proposed algorithm has time, compared with GWO, to track PV system conditions at speeds of 0.189 s and 0.21 s. Total power control accuracy in different PV system settings is 344, 65 W and 335,76 W according to the GWO. The findings suggest that the proposed algorithm is superior to that of the GWO in terms of accuracy and speed. In addition, there are slight oscillations around the proposed algorithm.

References

[1]. R. Elavarasan et al., "A Comprehensive Review on Renewable Energy Development, Challenges, and Policies of Leading Indian States With an International Perspective", IEEE Access, vol. 8, pp. 74432-74457, 2020.

[2]. A. Debnath, T. Olowu, I. Parvez, M. Dastgir and A. Sarwat, "A Novel Module Independent Straight Line-Based Fast Maximum Power Point Tracking Algorithm for Photovoltaic Systems", Energies, vol. 13, no. 12, p. 3233, 2020.

[3]. T. Zidane, M. Adzman, M. Tajuddin, S. Mat Zali and A. Durusu, "Optimal configuration of photovoltaic power plant using grey wolf optimizer: A comparative analysis considering CdTe and c-Si PV modules", Solar Energy, vol. 188, pp. 247-257, 2019.

[4]. M. Mao, L. Cui, Q. Zhang, K. Guo, L. Zhou and H. Huang, "Classification and summarization of solar photovoltaic MPPT techniques: A review based on traditional and intelligent control strategies",

Energy Reports, vol. 6, pp. 1312-1327, 2020.

[5]. G. Petrone, M. Luna, G. La Tona, M. Di Piazza and G. Spagnuolo, "Online Identification of Photovoltaic Source Parameters by Using a Genetic Algorithm", Applied Sciences, vol. 8, no. 1, p. 9, 2017.

[6]. M. Louzazni, A. Khouya, K. Amechnoue, A. Gandelli, M. Mussetta and A. Crăciunescu, "Metaheuristic Algorithm for Photovoltaic Parameters: Comparative Study and Prediction with a Firefly Algorithm", Applied Sciences, vol. 8, no. 3, p. 339, 2018.

[7]. B. Tan, X. Ke, D. Tang and S. Yin, "Improved Perturb and Observation Method Based on Support Vector Regression", Energies, vol. 12, no. 6, p. 1151, 2019.

[8]. U. Chauhan, B. Kumar, A. Rani and V. Singh, "Optimal Perturbation MPPT Technique for Solar PV System using Grey Wolf Optimization," 2019 International Conference on Computing, Power and Communication Technologies (GUCON), NCR New Delhi, India, 2019, pp. 589-592.

[9]. R. Kumar, S. Khandelwal, P. Upadhyay and S. Pulipaka, "Global maximum power point tracking using variable sampling time and p-v curve region shifting technique along with incremental conductance for partially shaded photovoltaic systems", Solar Energy, vol. 189, pp. 151-178, 2019.

[10]. A. Baba, G. Liu and X. Chen, "Classification and Evaluation Review of Maximum Power Point Tracking Methods", Sustainable Futures, vol. 2, p. 100020, 2020.

[11]. H. Mohammed, M. Kumar and R. Gupta, "Bypass diode effect on temperature distribution in crystalline silicon photovoltaic module under partial shading", Solar Energy, vol. 208, pp. 182-194, 2020.

[12]. M. Mohamed, A. Zaki Diab and H. Rezk, "Partial shading mitigation of PV systems via different meta-heuristic techniques", Renewable Energy, vol. 130, pp. 1159-1175, 2019.

[13]. K. Sundareswaran, S. Peddapati and S. Palani, "MPPT of PV Systems Under Partial Shaded Conditions Through a Colony of Flashing Fireflies," in IEEE Transactions on Energy Conversion, vol. 29, no. 2, pp. 463-472, June 2014.

[14]. A. Agbemuko, J. Domínguez-García, E. Prieto-Araujo and O. Gomis-Bellmunt, "Impedance Modelling and Parametric Sensitivity of a VSC-HVDC System: New Insights on Resonances and Interactions", Energies, vol. 11, no. 4, p. 845, 2018.

[15]. S. Mirjalili, S. Mirjalili and A. Lewis, "Grey Wolf Optimizer", Advances in Engineering Software, vol. 69, pp. 46-61, 2014. .

[16]. A. Dolara, F. Grimaccia, M. Mussetta, E. Ogliari and S. Leva, "An Evolutionary-Based MPPT Algorithm for Photovoltaic Systems under Dynamic Partial Shading", Applied Sciences, vol. 8, no. 4, p. 558, 2018.

[17]. A. Eltamaly, M. Al-Saud and A. Abo-Khalil, "Performance Improvement of PV Systems' Maximum Power Point Tracker Based on a Scanning PSO Particle Strategy", Sustainability, vol. 12, no. 3, p. 1185, 2020.

[18]. H. Lee and J. Yun, "Advanced MPPT Algorithm for Distributed Photovoltaic Systems", Energies, vol. 12, no. 18, p. 3576, 2019.

[19]. M. da Rocha, L. Sampaio and S. da Silva, "Comparative analysis of MPPT algorithms based on Bat algorithm for PV systems under partial shading condition", Sustainable Energy Technologies and

Assessments, vol. 40, p. 100761, 2020.

[20]. E. Dupont, R. Koppelaar and H. Jeanmart, "Global available solar energy under physical and energy return on investment constraints", Applied Energy, vol. 257, p. 113968, 2020.

[21]. M. Kermadi, Z. Salam, J. Ahmed and E. Berkouk, "An Effective Hybrid Maximum Power Point Tracker of Photovoltaic Arrays for Complex Partial Shading Conditions", IEEE Transactions on Industrial Electronics, vol. 66, no. 9, pp. 6990-7000, 2019

[22]. E. Mendez, A. Ortiz, P. Ponce, J. Acosta and A. Molina, "Mobile Phone Usage Detection by ANN Trained with a Metaheuristic Algorithm †", Sensors, vol. 19, no. 14, p. 3110, 2019.

[23]. R. Tascioni, L. Cioccolanti, L. Del Zotto and E. Habib, "Numerical Investigation of Pipelines Modeling in Small-Scale Concentrated Solar Combined Heat and Power Plants", Energies, vol. 13, no. 2, p. 429, 2020.

[24]. M. Premkumar and R. Sowmya, "An effective maximum power point tracker for partially shaded solar photovoltaic systems", Energy Reports, vol. 5, pp. 1445-1462, 2019.

[25]. H. Li, D. Yang, W. Su, J. Lu and X. Yu, "An Overall Distribution Particle Swarm Optimization MPPT Algorithm for Photovoltaic System Under Partial Shading", IEEE Transactions on Industrial Electronics, vol. 66, no. 1, pp. 265-275, 2019.

[26]. M. Neethu and R. Senthilkumar, "Soft Computing Based MPPT Controller for Solar Powered Battery Charger Under Partial Shading Conditions," 2019 Fifth International Conference on Electrical Energy Systems (ICEES), Chennai, India, 2019, pp. 1-6.

[27]. S. Ngo and C. -S. Chiu, "Simulation Implementation of MPPT Design under Partial Shading Effect of PV Panels," 2020 International Conference on System Science and Engineering (ICSSE), Kagawa, Japan, 2020, pp. 1-6.